Reliability analysis of claim data for quality claim management

Meena Watcharathiansakul

Submitted in partial fulfillment
of the requirements for the degree of

Doctor of Philosophy

The Graduate School of Information Systems
The University of Electro-Communications
Tokyo, Japan

Mar, 2017

Reliability analysis of claim data for quality claim management

博士論文審査委員会

主査	田中	健次	教授
委員	鈴木	和幸	特命教授
	大須賀	昭彦	教授
	植野	真臣	教授
	仁科	健	教授
	横川	慎二	准教授

Reliability analysis of claim data for quality claim management

Abstracts

Claims on quality problems are valuable sources of information to improve claim management. Addressing individual claim resolution and aggregating claim data analysis are focused for the claim management. After new products are released, claim management should be carried out as follows: detecting major quality problems as early as possible, performing immediate remedy, finding the root cause of problems, implementing measures for the root cause and then confirming their effects. For each step, both qualitative and quantitative analyses are important for improving claim management.

Due to having a particular cause per each claim, each claim has a specific number of claims per month. This thesis proposes two analysis methods focusing on this feature which are effective for the claim data analysis. One method is for detecting major quality problems, and the other is for examining effectiveness of actions taken. The former analysis has the advantage of accuracy and a timely detection. Cumulative Sum Control Chart (CUSUM) is applied for detecting major quality problems. The properties of CUSUM design parameters, which are not investigated in the previous research, are investigated in this thesis for drawing out a scheme of detection in a claim management. In the latter analysis, a comprehensive and significant testing method by using Quality Claim Management Matrix (QCMM) is proposed. Claim data over certain intervals for the analysis is required for the proposed method. In order to examine the effectiveness of actions taken, hypothesis tests are performed. Likelihood functions for grouped claim under the null and alternative hypotheses are developed and used to calculate the likelihood ratio statistic for testing the effectiveness of actions taken. In addition, the proposed method and the previous one are comparatively analyzed. Two application examples that were provided by two companies are used for the purpose of giving an illustration. Each example has a quality problem with a single cause.

The two proposed methods can be applied in a flexible way by using one or both of them. Moreover, this thesis provides CUSUM design parameters and power values of likelihood ratio test in tables, which cover a wide range of number of claims per month and are able to apply to various quality problems of products and their various claim rates. They are easy to be carried out and useful to analyze claim data corresponding to problems in any industrial world.

品質クレームマネジメントのための信頼性クレームデータ分析

要旨

品質問題に関する顧客からのクレームは、市場での品質や信頼性に関する貴重な情報源である。それらを扱うクレームマネジメントには、個々のクレームへの迅速かつ適切な対応と、技術的な解析などをはじめとする収集したクレームデータの分析とこれに基づくアクションが欠かせない。このようにクレームマネジメントプロセスの改善にとって、クレームデータの分析は重要である。新製品上市後のクレームマネジメントは、重要な品質問題の早期発見、応急対策、問題の根本原因の究明、根本原因対策の実施、対策効果の検証、の順に行われる。それぞれのステップでは、クレームマネジメントの向上のため、定性分析及び定量分析が求められる。

各クレームデータには固有の原因があり、そのことにより月次のクレーム数の期待値が定まる。本論文では、このことに着目したクレームデータ分析に有効となる二つの統計的分析手法を提案する。一つ目は重要な品質問題を早期発見するための手法である。正確かつタイムリーに重要な問題を発見することを狙いとして、累積和（CUSUM）管理図を用いた手法を提案する。そのために CUSUM 管理図の性質を検討し、クレームデータのモニタリングのための設計パラメータの設定方法を提案する。そして CUSUM 管理図と Shewhart 管理図を比較し、提案手法の性質を明らかにする。二つ目は、クレームへの対策が実施された後に、その効果の有意性を検証するための手法である。そのために品質クレームマネジメントマトリックス（QCMM; Quality Claim Management Matrix）を使用した包括的かつ統計的検証手法を提案する。この手法には、ある一定期間に渡るクレームデータが必要とされ、対策の効果の検証のために仮説検定を用いる。クレームに対する帰無仮説と対立仮説の下での尤度関数に基づいて、対策効果を検証するための尤度比検定を用いることを提案する。さらに、提案した手法と従来の手法を比較し、提案手法の性質を明らかにする。また二社から提供された二つの実データに基づいて、提案手法の有用性を示す。

提案する二つの手法は、それぞれを単独に用いても、組み合わせて用いても良く、柔軟に適用しうる。本論文では、様々な製品、様々なクレーム率を持つ場合など、どのような製品の品質問題にも適用可能な累積和（CUSUM）管理図の設計パラメータと尤度比検定の検出力への表を提示する。この表に基づく提案手法は、月ごとのクレーム数を広範囲に設定でき、どのような業種のクレーム問題と広範囲なクレーム発生率にも対応可能な有用な方法である。

Contents

Chapter 1 Introduction

Chapter 2 Statistics for detecting major quality problem

Chapter 3 Statistics for examining effectiveness of actions taken

Chapter 4 Application of the proposed methods

List of Figures

List of Tables

Chapter 1

Introduction

Overview

This chapter presents the general introduction to the thesis. Section 1.1 explains the concept of claim management. Section 1.2 introduces quality claim management matrix (QCMM). Section 1.3 outlines the principle of a conventional CUSUM. Section 1.4 outlines problems and motivation. Section 1.5 explains the purposes of the research. Section 1.6 reviews the literature. Section 1.7 and 1.8 explains the application examples and important notation respectively and Section 1.9 outlines the structure of the thesis.

1.1 Claim management

With the market globalization and the growth of competitiveness in the manufacturing sector, product quality has become an essential part of the product. In order to improve a product quality, companies take the initiative in tackling quality problems. Several quality management programs such as TQM, ISO9000 and Six Sigma are normally embedded into the business operations and adopted by many companies nowadays. Complaint management is a part of the ISO9000 standard. Both quality and complaint management are for improving customer satisfaction. A complaint related to a company generally means dissatisfaction with its products and process management that customers express, ISO10002 (2004). The interpretation of "claims" and "complaints" differs with each company or country. As shown in Figure 1.1, "complaints" are classified into two kinds, "claims" or "voices" in this thesis. "Claims" refer to dissatisfaction with some demands for the substantial resolution such as repair, exchange, discount, compensation for damage where a company should admit his fault and responsibility to customers. In contrast, "voices" mean dissatisfaction without any demand that a company should owe the responsibility to customers. Furthermore, claims are divided into two categories, which are related or not related to quality problems. Claims related to quality problems are classified into two categories, which are related or not related to product lifetime. The claims related to product lifetime include claims concerning safety and claims not concerning safety. This thesis focuses on the claims concerning product lifetime which incurred high warranty cost and /or gave customers dissatisfaction. Some of serious claims concerning safety have a risk of causing a serious accident. However, claims concerning safety are not considered in this thesis.

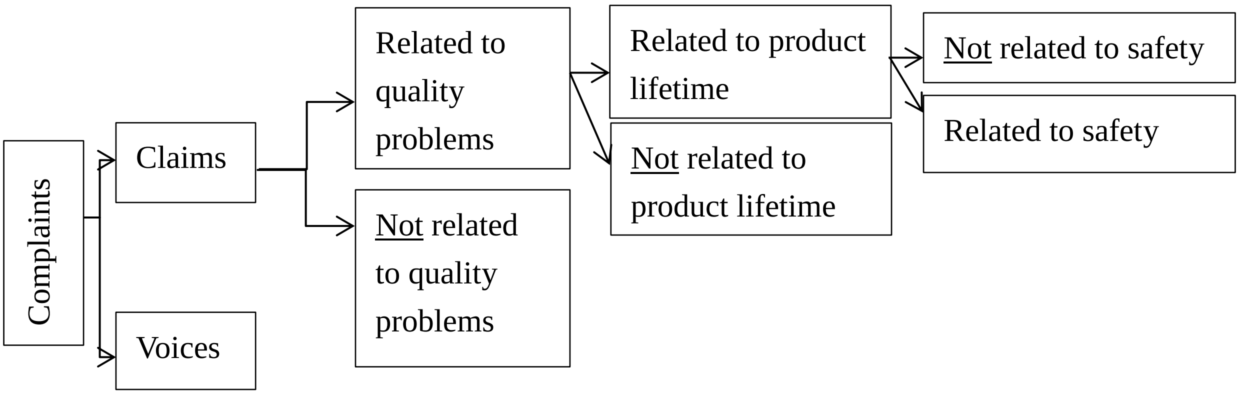

Figure 1.1 Classification of complaints based on a certain company's example

Claim management is the process of handling claims related to products in an organization. It has two main functions: 1) addressing individual claim resolution and 2) aggregating claim data analysis, discussed by John and Richard (1994). Generally, a key to resolve individual claims is to design claim management process for eliminating customers' dissatisfaction immediately. There are many literatures about this area such as Behrens, Wilde and Hoffman (2007), and ISO10002 (2004). Even among them, 8D method which was developed by an automobile industry is best known as a practical method for handling complaints. It is an international standard which spreads all over the industry. The 8D method is a problem solving approach which contains an eight step procedure for the management of claims or complaints. It serves as a documentation of countermeasures taken for claimants or complainants. In addition to resolving individual claims, analyzing aggregate claims is focused for acquiring accuracy, formulating managerial strategies, preventing claim recurrence and reducing the number of claims. Some practitioners are interested in quantitative analysis and others are interested in qualitative analysis. Both of them are necessary for improving claim management. After new products are released, claim management should be performed as follows: detecting major quality problems as early as possible, performing immediate remedy, finding a root cause of the problems, implementing measures for the root cause and then confirming their effects. For each step, both qualitative and quantitative analyses are important. Problem solving approach, FMEA, FTA and root cause analysis (RA) are extensively used and integrated for improving a claim management process in many companies. The conventional research about the claim management process is carried out by integrating the practiced methodologies. Bosch and Enriquez (2005) proposed customer complaint management system model (CCMS) that integrated practice-tested methodologies such as QFD, Problem Solving, and FMEA. There are only a few related reports on developing a new technique that deals with claim management.

1.2 Quality Claim Management Matrix (QCMM)

Kano, Boonthanom and Merchant (2013) proposed five point-in-time measures for monitoring the quality claim management process: 1) market release of new product (MR), 2) first claim occurrence (FCO), 3) major quality problem registration (MQPR), 4) recurrence prevention completion (RPC), and 5) recurrence claim occurrence (RCO). Their approach with the point-in-time measures is used to group claim data in the form of two-way contingency table, which is called quality claim management matrix (QCMM). The QCMM is used to group claim data along two axes using the same five time points for each axis, as shown in Table 1.1. The five time intervals (P1–P5) are the intervals corresponding to the five point-in-time measures described above. The horizontal axis shows claim occurrence, and the vertical axis shows product shipment. Each claim is assigned to the appropriate cell of the matrix. MQPR is used to distinguish major claims from minor ones to enable the prioritization of two proposed intermediate actions before RPC: stop usage and stop shipment. These containment actions are more or less identical to the short-term containment actions in the 8-D method, proposed by Behrens et al. (2007). The latter, however, are implemented uniformly without prioritization of major problems the same with MQPR, proposed by Kano et al. (2013). MQPR is the most appropriate method for claims that are difficult to find out the root cause and/or high impact and/or high frequency. According to Kano et al. (2013), claims on units having the same problem would likely increase as the number of units increases if actions are not taken such as identifying major quality problems, registering them, and implementing the “stop usage” and/or “stop shipment” actions.

Table 1.1 Structure of QCMM (Kano, Boonthanom, and Merchant, 2013)

		Time of claim occurrence					
		P1: MR – FCO	P2: FCO – MQPR	P3: MQPR – RPC	P4: RPC – RCO	P5: RCO	
Time of product shipment	P1: MR – FCO	C1 A_i	C1 A_i	C1 A_i A_p	C2 B_i B_p	C3	Action for C3
	P2: FCO – MQPR		C1 A_i	C1 A_i A_p	C2 B_i B_p	C3	
	P3: MQPR – RPC			C1 A_i A_p A_f	C2 B_i B_p	C3	
	P4: RPC – RCO				C2 B_f	C3	
	P5: RCO					C3	

A claim that occurred after FCO and before MQPR on a unit that shipped between MR and FCO would be assigned to the cell in the second column and first row. Claims in the matrix are separated into three groups: C1, C2, and C3. C1 represents claims that occurred before RPC and for which immediate remedial actions (represented by A) are taken. C2 represents claims that occurred after RPC and for which recurrence prevention actions (represented by B) are taken.C3 represents claims that occurred after RCO and for which actions for C3 are taken. The A or B categorization depends on the type of customer: individual claimant, potential claimant, and future customer. The subscript (i, p, or f) following the A or B shows the action taken for a claim, which depends on the claim type.

1) Individual claimant (i): actions are taken to correct the problem that customers appeal for. Actions for A_i such as repairs and for B_i such as on-call maintenance should be considered.

2) Potential claimants (p): actions are applied to other units that may suffer a similar problem. Additional actions for A_p such as stopping usage can be applied. Additional actions for B_p, such as performance of onsite-maintenance, recall, and replacement should be considered.

3) Future customers (f): in order to prevent the same problem from occurring to future customers, actions should be applied to similar products as well as manufacturing process. Additional actions for A_f, such as a stop of shipment, and for B_f such as re-design, re-process and revision of operating standard should be considered.

These notations were developed by Kano et al. (2013) and are used here in QCMM to indicate the types of action that correspond to the types of customers. The number of claims is mapped according to time of claim occurrence and time of product shipment in the form of QCMM. The number of claims in each time interval (P1-P5) is used to examine the effectiveness of recurrence prevention actions. Once the action for the claim type is assigned after MQPR and after RPC, the number of claims after MQPR and RPC on product shipped in each interval are counted and used to determine the effectiveness of the actions. They explain that the smaller number of claims in each interval expresses the better effectiveness of actions taken.

1.3 The principle of a conventional CUSUM

Cumulative sum control charts (CUSUM) were first proposed by Page (1954) and have been studied by many authors such as Hawkins and Olwell (1998), and Woodall (1993). This section concentrates on CUSUM for count data which shows how it can be used for monitoring a number of claims. It is possible to devise CUSUM procedures for other variables, such as binomial variables for modeling fraction nonconforming.

It has been assumed that a number of claims in observation time n_t follow a Poisson distribution. A persistent increase in number of claims is expected to detect from an in-control state $\lambda_0 N$ to an out-of-control state $\rho_1 \lambda_0 N$. The CUSUM is given by (1.1)

$$G(t) = \max(0,\ G(t-1) + n_t - k), \tag{1.1}$$

where $k = \frac{\rho_1 \lambda_0 N - \lambda_0 N}{\log(\rho_1 \lambda_0 N) - \log(\lambda_0 N)}$ or $\left(\frac{\rho_1 - 1}{\log \rho_1}\right) \lambda_0 N$,

$\lambda_0 N$ is number of claims under in-control state,

$\rho_1 \lambda_0 N$ is number of claims under out-of-control state.

An increase in number of claims is signaled if $G(t) > h$.

CUSUM starts out at its initial state $G(0) = 0$. From the starting point, it may stay on the axis, or it may into positive values. Therefore, $G(t)$ will end in one of two ways of which CUSUM returns to zero, or it crosses the threshold. When the chart crosses the threshold, this indicates that an increase in number of claims has occurred. Then actions should be taken to diagnosis the increasing. Generally CUSUM be restarted after that. The whole sequence from the starting point to the CUSUM crossing the threshold is "Run". The observation time from the starting point up to the point of crossing the threshold for the first time is "Run length". It is also called "time-to-signal". The run length is a random variable that has a mean, a variance and a distribution. The mean is called the average run length or *ARL*.

CUSUM sometimes signals even though an increase in number of claims does not occur (in-control state). This false alarm is analogous to a Type I error in classical hypothesis testing. These false alarms are undesirable, as they cause unjustified actions and/or disrupt operations looking for nonexistent special causes. Generally, Type I error should be kept as low as possible. Or, the *ARL* under in-control state should be as long as possible. A Type II error in classical hypothesis testing also has an analog in a CUSUM. It is the CUSUM remaining no signal even though an increase in number of claims has occurs (out-of-control state). This error may result in a substantial number of claims. If there has been an increase in number of claims serious enough to have practical implications, the CUSUM is expected to detect the increasing as soon as possible. The *ARL* under out-of-control state should be kept as short as possible. Therefore, a CUSUM needs long *ARL* under in-control state and short *ARL* under out-of-control state. These objectives are conflict, so it is necessary to make trade-off between them. This is also exactly analogous to the trade-offs between Type I and Type II errors in classical hypothesis testing.

A CUSUM is designed by choosing a pair value of (k, h) that gives some acceptable long in-control *ARL* and short out-of-control *ARL*. This can be done using tables, graphs or software. It is generally designed on the basis of the *ARL*, however, the probability distribution and the cumulative distribution of run length are also used. An approximation of *ARL* can be calculated by using the integral equation approach such as the description by Goel, A.L. and Wu, S.M. (1971), Markov chain methodology such as the explanation by Brook and Evans (1972), and simulation.

The CUSUM is superior to quickly detect small to moderate change among all procedures which have the same false alarm rate or the same in-control *ARL*. In other words, CUSUM has the smallest expected run length out-of control. This is the optimal property of CUSUM. See Hawkins and Olwell (1998) for a more detailed discussion of CUSUM methods, their properties and further references.

1.4 Problem and motivation

A problem of a certain company has been shown in Figure 1.2. As root cause of the problem was identified and recurrence prevention in a production process was performed completely. A conventional analysis by the company revealed that the claim rate was not reduced. The following is the detail information about the analysis that was conducted by the company. Claims on quality problems with a single cause were aggregated each month over 30 months. The total number of units shipped up to six consecutive months was 1200 as shown in Table 1.2. The lag time between manufacturing and shipping was ignored. Fig. 1.2 shows the cumulative claims per unit that correspond to the claim data in Table 1.2. The cumulative claim rate for the first 6 months after RPC was lower than that before RPC. However, after 13 months from RPC, in other words, at the 19th month, the cumulative claim rate became higher and then continuously increased.

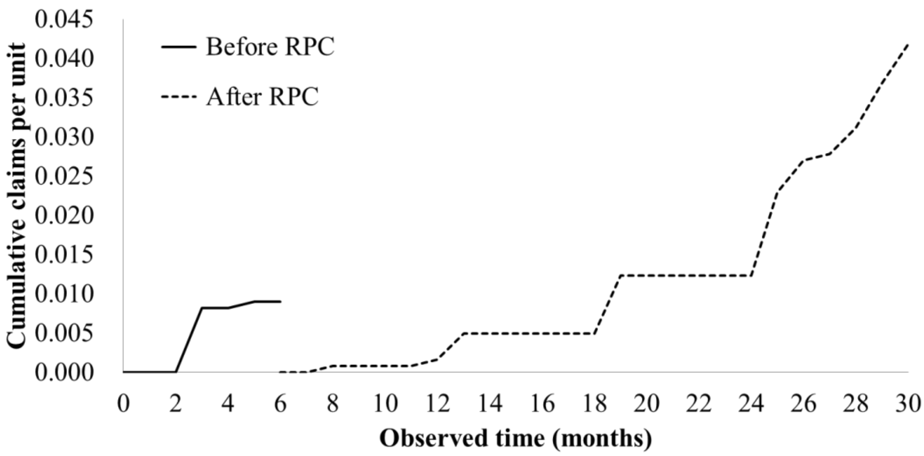

Figure 1.2 Cumulative claims per unit before and after RPC, where RPC stands for recurrence prevention completion

Table 1.2 Example II: Number of claims over 30-month period for units shipped over six consecutive months

Month of product shipment	No. of units shipped	Monthly claim occurrence					RPC ↓																								
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	200	0	0	**2**	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	**2**	0	0	0	0	0	**1**	**1**	0	0	0	0
2	200	-	**2**	**1**	0	**1**	0	0	0	0	0	0	0	**1**	0	0	0	0	0	**3**	0	0	0	0	0	**1**	0	0	0	**1**	0
3	200	-	-	**1**	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	**1**	0	0	0	0	0	**1**	0	0	0	0	**1**
4	200	-	-	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	**3**	**2**	**1**	**1**	**2**	**2**
5	200	-	-	-	-	0	0	0	**1**	0	0	0	**1**	**1**	0	0	0	0	0	**1**	0	0	0	0	0	**3**	**1**	0	**1**	**2**	**2**
6	200	-	-	-	-	-	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	**4**	**1**	0	**2**	**2**	**1**
		0	**2**	**4**	**0**	**1**	**0**	**0**	**1**	**0**	**0**	**0**	**1**	**4**	**0**	**0**	**0**	**0**	**0**	**9**	**0**	**0**	**0**	**0**	**0**	**13**	**5**	**1**	**4**	**7**	**6**

The conventional analysis did not provide enough information on what type of actions taken was effective. Kano et al. (2013) proposed quality claim management matrix (QCMM) with an important point-in-time measure of major quality problems registration (MQPR) to analyze claim data (Table 1.2). Kano et al. (2013) found that MQPR could effectively reduce claims and QCMM could be comprehensively used to evaluate the effectiveness of actions taken in claim management process. However, Kano et al. (2013) did not mention a method of identifying MQPR. MQPR is set by the company's rule of thumb. This method is neither analytical nor applicable for all companies and for all problems. QCMM has a comprehensive structure, however, its evaluation approach is not considered in a statistical significant way. It may not provide enough information to decide action needed for an improvement. In other words, having no significant change in number of claims may cause unjustified actions and/or may affect the number of claims. From the above two viewpoints, therefore alternative solutions needed to be explored in this thesis.

1.5 Purpose of the research

The objective of this thesis is to propose two statistical methods and to discuss statistical properties of the two proposed methods. One of the proposed methods is for detecting major quality problems and the other is for examining effectiveness of actions taken by effectively using Quality Claim Management Matrix (QCMM). By utilizing the two proposed methods, some existing problems discussed in Section 1.4 are overcome. Both proposed methods are focused on the claims that are related to product lifetime but not related to safety.

The former statistical method is to focus on an increase in number of claims. the sooner an increase in number of claims can be detected, the sooner major quality problems can be registered. CUSUM is proposed for the detection.

The latter statistical method is designed for examining effectiveness of actions taken. Likelihood ratio test by using Quality Claim Management Matrix (QCMM) is proposed. The two proposed methods can be applied in a flexible way. It enables a practitioner to use one or both methods. This thesis uses Example I for illustrating the case of which the two proposed methods are applied together and Example II for illustrating the case in which each method is applied independently. Moreover, this thesis provides CUSUM design parameters of detection and power values of likelihood ratio test in tables, which covers a wide range of expected number of claims per month and is able to apply to various quality problems of products and their various claim rates. The CUSUM design parameters of detection and power values of likelihood ratio test are useful to implement the two proposed methods for improving claim management.

1.6 Literature review

Warranty claim data analysis methods are adopted to analyze claim data in this thesis. Many warranty data issues have been studied. Lawless (1998) described general ideas of statistical methods for warranty claim data. Warranty claim data analysis for case studying in reliability was outlined by Iskandar and Blischke (2003). Suzuki (1985 a, b) dealt with problems arising in the field and warranty claim data. Lawless, Crowder and Lee (2012) and Wu and Meeker (2002) described control chart methods for detecting warranty claim data.

1.6.1 Method for detecting major quality problems

As mentioned before, a major quality problem should be detected and then actions for units shipped and units under shipment should be taken. These actions taking into consideration future claims are proactive approach and useful for preventing recurrence claims and/or mitigating negative impacts. Therefore, if there is a method for detecting major quality problems, the method would be particularly meaningful with respect to the improvement of claim management in the industrial world.

A method for detecting a major quality problem which leads to safety differs by companies. Some companies recently focus on number of claims and then sort the claims by the degree of human injury, as a human injury tends to attract public interest. Additionally, claims which cause human injuries hurt the product's reputation and company's image. Therefore, companies are interested in a risk ranking to identify major quality problems. Interested readers may refer to the discussion and explanation that are shown by ISO/IEC Guide 51. However, according to a certain company, most of the claims actually belong to the claims which are not related to safety. Numerous claims incur high warranty cost. In order to reduce the number of claims, a significant increase in number of claims or claim rate should be identified for detecting a major quality problem. In general, the method for detecting the above change comprises three scenarios based on acquired parameters: (1) all parameters before change and after change are specified a priori; (2) the parameter before change is specified, but the parameter after change is not specified; and (3) neither the parameter before change nor the parameter after change is specified. This thesis focuses on the first scenario. Actually, a manufacturing company such as automobile industry has the information on the parameter before change by the previous model, and the information on new model is determined by the threshold of the past experiences of the problematic models. Therefore, the parameter before change and after change can be specified by a priori. The CUSUM is applied in this thesis because it has optimal property for such scenario. For the second or the third scenario, further study such as "machine learning" is important. See Hawkins and Qiu (2003) for a more detailed discussion of the method for detecting changes.

The CUSUM procedures are now one of the most well-known methods for sequential data which has been widely used for monitoring in a manufacturing process. Hawkins and Olwell (1998) proposed a conventional CUSUM approach which is usually applied to a stationary setting. An observation corresponding to a given time is required to be unchanged. Biswas and Kalbfleisch (2008) and Gandy, Kvaloy, Bottle and Zhou (2010) discussed CUSUM procedures for applying to health care and public health monitoring and surveillance. The data that are often observed in these applications are non-stationary setting, or have some built-in pattern when new observations are added. Lawless, Crowder, and Lee (2012) presented CUSUM procedures by using updated warranty data for monitoring of reliability and warranty data. They showed the analysis in different scenarios for detecting moderate and large increase in claim rate. They also presented comparative analysis between CUSUM procedures and Shewhart-type procedures which were proposed by Wu and Meeker (2002). They found that Shewhart-type procedures provide quick detection of large increase in claim rate although they are hard to design. However, CUSUM procedures are simpler to design and provide superior power in many practical settings, in particularly, timely detection of small to moderate increase in claim rate. For easily drawing out a scheme of detection, CUSUM design approach is indispensable. CUSUM design approach proposed by Lawless et al. (2002) was only a general idea, therefore, it should be developed.

1.6.2 Method for examining effectiveness of actions taken

When a major quality problem is detected, the monthly claims are aggregated into specific time intervals for creating QCMM as shown in Table 1.1. Once the company examines the effectiveness of actions taken, the action that is needed for improving the claim management process can be identified. The collection of claim data over certain intervals for use in the analysis is required for this examination. In order to decide whether or not the effectiveness of actions taken exists, a statistical methodology involved in decision making of the above situation which is known as hypothesis testing is proposed. Moreover, in order to examine main processes of claim management, this thesis proposes the hypothesis testing on QCMM. A lot of early hypothesis testing methods such as *t* tests or *F* tests are dominated by the normal outcome data. In the case of count data used in this thesis, the collection of the count data in the form of QCMM is complicated. Therefore, likelihood based on modeling is indispensable for simplifying. For hypothesis testing, likelihood function is used directly, which is known as likelihood ratio test. The likelihood ratio test is popular choices because it is uniformly most powerful test in many practical situations. Here, likelihood functions for grouped claim under the null and alternative hypotheses are developed and used to calculate the likelihood ratio statistic for examining the effectiveness of actions taken. Then power value $(1-\beta)$ indicates a significant level of effectiveness of actions taken. The proposed method by Kano et al. (2013) and this thesis are different. Kano et al. (2013) referred the number of claims in each region and not mathematically indicated the effectiveness of actions taken. However, the proposed method in this thesis refers to the power value $(1-\beta)$.

1.7 Application examples

Two application examples of two businesses are used here for illustration purposes. Each example has quality problems with a single cause. For simplicity, the lag time between production and shipment is not considered. For detecting major quality problems, in Example I, actual monthly claim data is used as shown in Table 1.3. 1250 units were produced each month. The average claim rate which was estimated based on the past claim data, was 0.0055 (41÷7500) per unit per month. In example II, actual claim data is used as shown in Table 1.2. 200 units were produced each month. The average claim rate which was estimated based on the past claim data, was 0.0017(7÷4200) per unit per month. The number of units shipped in each month is assumed to be the same. The average claim rate for the product should be derived from the past claim instances on products or determined by the company’s expectation.

Table 1.3 Example I: Number of claims over 5 months period for units shipped over 5 consecutive months

RPC

Month of product shipment	No. of units shipped	Monthly claim occurrence				
		1	2	3	4	5
1	1250	1	16	8	5	0
2	1250	-	6	1	2	0
3	1250	-	-	0	2	0
4	1250	-	-	-	0	0
5	1250	-	-	-	-	0
		1	22	9	9	0

For examining effectiveness of actions taken, in Example I, grouped claim data is aggregated by obtaining the point-in-time measure of MQPR from the above proposed method. Then QCMM is formed to examine effectiveness of actions taken as shown in Table 4.2. In Example II, grouped claims and aggregated the number of unit shipped in the form of a QCMM is used by assuming that MQPR is pre-defined by the company using any method as shown in Table 1.4. As for MQPR and RPC, they occurred within four months and six months respectively after MR. After RPC, claim data was collected for eight months. RCO was not identified by the company.

Table 1.4 QCMM for Example II

2 month 2 month 2 months 8 month

		No. of unit shipped in the intervals	Time of claim occurrence			
			P1: MR - FCO	P2: FCO - MQPR	P3: MQPR-RPC	P4: RPC ~
Time of product shipment	P1: MR – FCO	400	2	3	1	2
	P2: FCO – MQPR	400	-	1	0	1
	P3: MQPR – RPC	400	-	-	0	3
	P4: RPC ~	1600	-	-	-	-

1.8 List of notation

MR	: market release
FCO	: first claim occurrence
MQPR	: major quality problem registration
RPC	: recurrence prevention completion in a production process
RCO	: recurrence claim occurrence
i	: month of unit shipment, i = 1,2,…I, where I is the total number of months in which units are shipped
t	: observation time
T	: total number of observation months
N_i	: number of units shipped in month i
a	: age index, a = 1,…, T, where a represents month in service
λ	: expected number of claims per unit at age a; i.e., claim rate
$n_{i,a}$	: number of claims at age a for units shipped in month i
λ_0	: claim rate under the null hypothesis; i.e., null claim rate
ρ_1	: the multiple of the null claim rate
λ_1	: claim rate under the alternative hypothesis, where $\lambda_1 = \rho_1 \lambda_0$
λ_g	: claim rate under different multiple of null claim rate, where $\lambda_g \neq \lambda_1$
n_t	: total number of claims in observation time t
$\widetilde{N}$	: total number of units shipped up to time t
c	: multiplier of standard deviation for Shewhart procedures
$Y(t)$	: transition probability matrix for the process at time t
Z	: absorbing state transition matrix
$G(t)$	: CUSUM statistic
h	: threshold for CUSUM chart
ARL_0	: average run length under H_0
ARL_g	: average run length under λ_g
k	: index denoting time interval, $k \in \{1,2,3\}$
l	: index denoting product shipment interval, $l \in \{1,2,3\}$
Q_k	: specific time interval and its length is denoted by $\bar{Q}_k$
M_l	: number of units shipped in Q_l
$\mu_{l,k}$	: expected claim rate in Q_k on units shipped in Q_l
$m_{l,k}$	: number of claims in Q_k on units shipped in Q_l
u	: effective stop usage rate ($0 \le u \le 1$ where u = 1.0 is the maximum value)

v : effective stop shipment rate ($0 \leq v \leq 1$ where $v = 1.0$ is the maximum value)

q : effective recurrence prevention rate ($0 \leq q \leq 1$ where $q = 1.0$ is the maximum value)

1.9 Structure of the Thesis

The structure of the remainder of the thesis is as follows.

Chapter 2 presents statistics and properties for detecting major quality problems. A general structure of monthly claim data is used. Comparative analysis of CUSUM and Shewhart procedures is discussed.

Chapter 3 shows statistics and properties for examining the effectiveness of actions taken. A grouped claim data is used for the analysis.

Chapter 4 illustrates the proposed methods by using two application examples.

Chapter 5 gives concluding remarks concerning the thesis. Some recommendations for the future work and development are proposed as well.

Finally, Appendix A provides relevant parameters for detecting major quality problems, Appendix B provide relevant parameters for examining effectiveness of actions taken.

Chapter 2

Statistics for detecting major quality problems

Overview

This chapter describes a method to identify a significant increase in number of claims which is used for detecting major quality problems. For this approach of the detection, a model of monthly claim data is required in order to analyze claim data. A basic model of monthly claim data is introduced in Section 2.1. CUSUM procedures and the difference of CUSUM design approach between this thesis and Lawless et al. (2012) are discussed in Section 2.2 and 2.3 respectively. The properties of CUSUM are discussed in Section 2.5. Comparative analysis between CUSUM procedures and Shewhart procedures is shown in Section 2.6 by using the outlined CUSUM procedures (Section 2.2) and the outlined Shewhart procedures (Section 2.4).

2.1 Model of monthly claim data

- i : month of unit shipment, $i = 1,2,\ldots I$, where I is the total number of months for which units are shipped
- t : observation time
- T : total number of observation months ($T \geq I$)
- N_i : number of units shipped in month i
- a : age index, $a = 1,\ldots, T$, where a represents month in service,
- λ : expected number of claims per unit at age a; i.e., claim rate
- $n_{i,a}$: number of claims at age a for units shipped in month i
- λ_0 : claim rate under the null hypothesis; i.e., null claim rate
- λ_1 : claim rate under the alternative hypothesis
- n_t : total number of claims in observation time t, where $n_t = \sum_{i=1}^{\min(I,t)} n_{i,t-i+1}$

It is assumed that λ is constant claim rate at each age a. Table 2.1 illustrates the general structure of monthly claim data. The number of claims at age a for units shipped in month i is assumed to follow a Poisson distribution with λN_i. The probability mass function of the number of claims is expressed as follows,

$$Pr(n_{i,a}) = \frac{e^{-\lambda N_i}(\lambda N_i)^{n_{i,a}}}{n_{i,a}!} \quad . \tag{2.1}$$

Table 2.1 Structure of monthly claim data

Month of unit shipment (i)	No.of units Shipped in month i (N_i)	Observation time (t)							
		1	2	…	i	…	I	…	T
1	N_1	$n_{1,1}$	$n_{1,2}$	…	$n_{1,i}$	…	$n_{1,I}$	…	$n_{1,T}$
2	N_2		$n_{2,1}$	…	…	…	…	…	$n_{2,T\text{-}1}$
…	…			…	…	…	…	…	…
i	…				$n_{i,1}$	…	$n_{i,I\text{-}i\text{-}1}$	…	$n_{i,\,T\text{-}i\text{-}1}$
…	…					…	…	…	…
I	N_I						$n_{I,1}$	…	$n_{I,T}$
		n_1	n_2	…	…	…	n_I	…	n_T

The estimation of claim rate in each month can be expressed as

$$\hat{\lambda}_t = \frac{n_t}{\sum_{i=1}^{\min(I,t)} N_i} \quad , \tag{2.2}$$

The average claim rate of each example in this thesis can be estimated as

$$\hat{\lambda} = \frac{\sum_{t=1}^{T} \lambda_t}{T} \quad . \tag{2.3}$$

2.2 CUSUM procedures

2.2.1 CUSUM statistics

Lawless et al. (2012) presented the CUSUM procedures for monitoring warranty claims. The procedures outlined a way to compute CUSUM statistics as follows, CUSUM statistics denoted as $G(t)$ in (2.4) are obtained from likelihood ratio statistics for testing a simple null hypothesis versus a simple alternative hypothesis. The likelihood ratio statistics denoted as $W(t) - W(t-1)$ can be formulated from a log likelihood function based on claims up to time t.

CUSUM statistic can be shown as

$$G(t) = max\{0, G(t-1) + W(t) - W(t-1)\}, \tag{2.4}$$

where $t \geq 0$, $G(0) = 0$.

The formulation of likelihood ratio statistics can be explained as follows.

The log likelihood function can be written as

$$logL(T, \lambda) = -\sum_{i=1}^{I} \sum_{a=1}^{T-i+1} \lambda N_i + \sum_{i=1}^{I} \sum_{a=1}^{T-i+1} n_{i,a} \log(\lambda N_i). \tag{2.5}$$

A null and an alternative hypothesis are considered as shown in (2.6). λ_0 is used for the null hypothesis, which indicates the known claim rate specified by the manufacturer. $\rho_1 \lambda_0$ is used for the alternative hypothesis, where ρ_1 is the multiple of the claim rate under the null hypothesis, and what is more, ρ_1 represents the rate of increase in the claim rate. Particularly, the rate of increase ρ_1 from the first month of unit shipped onward is focused. An estimation of ρ_1 is not required, however, the choice of ρ_1 should be designed by compromise in order to provide some suitable properties for a monitoring scheme. The choice is common in monitoring schemes such as Biswas and Kalbfleisch (2008) and Gandy, Kvaloy, Bottle and Zhou (2010).

$$H_0: \lambda = \lambda_0; \; H_1: \lambda \geq \lambda_1 \text{ where } \lambda_1 = \rho_1 \lambda_0. \tag{2.6}$$

The log likelihood function of the null hypothesis and the alternative hypothesis can be written as

$$logL(T,H_0) = -\sum_{i=1}^{I}\sum_{a=1}^{T-i+1} \lambda_0 N_i + \sum_{i=1}^{I}\sum_{a=1}^{T-i+1} n_{i,a}\log(\lambda_0 N_i), \tag{2.7}$$

$$logL(T,H_1) = -\sum_{i=1}^{I}\sum_{a=1}^{T-i+1} \rho_1\lambda_0 N_i + \sum_{i=1}^{I}\sum_{a=1}^{T-i+1} n_{i,a}\log\left(\rho_1\lambda_0 N_i\right). \tag{2.8}$$

The likelihood ratio (LR) statistics (2.9) and (2.10) are computed from (2.7) and (2.8), and can be written as

$$\begin{aligned} W(t) &= -2\left(\frac{logL(T,H_0)}{logL(T,H_1)}\right) \\ &= 2\left\{\log(\rho_1)\sum_{i=1}^{I}\sum_{a=1}^{T-i+1} n_{i,a} - (\rho_1 - 1)\sum_{i=1}^{I}\sum_{a=1}^{T-i+1} \lambda_0 N_i \right\}, \end{aligned} \tag{2.9}$$

$$W(t-1) = 2\left\{\log(\rho_1)\sum_{i=1}^{I}\sum_{a=1}^{T-i} n_{i,a} - (\rho_1 - 1)\sum_{i=1}^{I}\sum_{a=1}^{T-i} \lambda_0 N_i \right\}, \tag{2.10}$$

$$\begin{aligned} W(t) - W(t-1) = 2\log(\rho_1)\Bigg\{&\left\{\sum_{i=1}^{I}\sum_{a=1}^{T-i+1} n_{i,a} - \sum_{i=1}^{I}\sum_{a=1}^{T-i} n_{i,a}\right\} - \\ &\frac{(\rho_1 - 1)}{\log(\rho_1)}\left\{\sum_{i=1}^{I}\sum_{a=1}^{T-i+1} \lambda_0 N_i - \sum_{i=1}^{I}\sum_{a=1}^{T-i} \lambda_0 N_i\right\}\Bigg\} \end{aligned} \tag{2.11}$$

Since ρ_1 is a specified constant, the $2\log(\rho_1)$ term in (2.11) is eliminated for simplifying. The equation in (2.11) is re-written as follows.

$$\begin{aligned} W(t) - W(t-1) = &\left\{\sum_{i=1}^{I}\sum_{a=1}^{T-i+1} n_{i,a} - \sum_{i=1}^{I}\sum_{a=1}^{T-i} n_{i,a}\right\} - \\ &\frac{(\rho_1 - 1)}{\log(\rho_1)}\left\{\sum_{i=1}^{I}\sum_{a=1}^{T-i+1} \lambda_0 N_i - \sum_{i=1}^{I}\sum_{a=1}^{T-i} \lambda_0 N_i\right\} \end{aligned} \tag{2.12}$$

When I = 1, the equation (2.12) is expressed as follows,

$$W(t) - W(t-1) \quad = n_{1,t} - \ k \text{, where } k = \frac{(\rho_1 - 1)}{\log(\rho_1)} \lambda_0 N_i. \tag{2.13}$$

When I = 1, the equation (2.13) is the same as the conventional CUSUM expressed in (1.1). As mentioned in Section 1.3, k is generally used as a design parameter for the conventional CUSUM. Instead of using k, this thesis uses a design parameter (ρ_1). To focus on $I \geq 1$, a total number of months for which units have been shipped is more than one month, expected numbers of claims for $\left\{\sum_{i=1}^{I} \sum_{a=1}^{T-i+1} \lambda_0 N_i \ - \sum_{i=1}^{I} \sum_{a=1}^{T-i} \lambda_0 N_i \right\}$ in (2.12) are not constant and they depend on the value of I. As a result, a design parameter which is calculated by $\frac{(\rho_1 - 1)}{\log(\rho_1)} \left\{\sum_{i=1}^{I} \sum_{a=1}^{T-i+1} \lambda_0 N_i \ - \sum_{i=1}^{I} \sum_{a=1}^{T-i} \lambda_0 N_i \right\}$ is difficult to define. Therefore, this thesis uses the parameter of ρ_1 without multiplication by the term of $\left\{\sum_{i=1}^{I} \sum_{a=1}^{T-i+1} \lambda_0 N_i \ - \sum_{i=1}^{I} \sum_{a=1}^{T-i} \lambda_0 N_i \right\}$ as one of design parameters. In addition, the total number of months for which units have been shipped (I) also should be defined as one of the other design parameters in Appendix A.

The above $G(t)$ in (2.4) obtained from the LR statistics (2.12) has the true number of claims for $\sum_{i=1}^{I} \sum_{a=1}^{T-i+1} n_{i,a} - \sum_{i=1}^{I} \sum_{a=1}^{T-i} n_{i,a}$ by considering H_0 versus H_1, which expresses a fixed multiple of the null number of claims. In the following subsection, the properties of CUSUM are also considered under the assumption that the number of claims for $\sum_{i=1}^{I} \sum_{a=1}^{T-i+1} n_{i,a} - \sum_{i=1}^{I} \sum_{a=1}^{T-i} n_{i,a}$ is independent Poisson random variable with the true number of claims $\lambda_g N_i$, where $\lambda_g N_i$ is $\rho_g \lambda_0 N_i$ corresponding to multiple of the null number of claims, that is, ρ_g times $\lambda_0 N_i$.

To implement the CUSUM procedures, $G(t)$ is monitored until it crosses over a fixed threshold h. It indicates that the number of claims is out of control. τ is the observation time t until the $G(t)$ just crosses over the threshold h,

$$\tau = \inf\{\ t > 0:\ G(t) \geq h\}. \tag{2.14}$$

2.2.2 CUSUM design

The term "Probability of a signal by time or Signal probability" was used by Lawless, et al. (2012) and is also used in this thesis. It accumulates all of the probability of a signal (run length) less than or equal to time. The probability of a signal by time is expressed as follows.

Lawless, et al. (2012) outlined the probability of a signal approach to provide some acceptable values by time under both the null and alternative hypotheses based on (2.5).

As mentioned by Gandy et al. (2010), the general CUSUM methodology and the Markov chain calculation work for a CUSUM chart against proportional alternatives that is a true number of claims which is the fixed multiple of the null number of claims. Besides the above cases where the system is always under the null or alternative hypotheses, this thesis investigates the cases where the true number of claims being a different multiple of the null number of claims. This thesis adopts the framework of Lawless et al. (2012) and Gandy et al. (2010) using the probability of a signal by time as well as the average run length (*ARL*) for choosing a CUSUM design plan. The probability of a signal by time is outlined in (2.15) and *ARL* as follows;

$$P(\tau, h, \rho_1) = Pr(\text{ signal by time } \tau) = 1 - Pr(G(1) < h,\ldots, G(t) < h), \tag{2.15}$$

$$\gamma(\tau, h, \rho_1) = Pr(\text{ first signal is at } \tau) = P(\tau, h, \rho_1) - P(\tau - 1, h, \rho_1). \tag{2.16}$$

From (2.16), *ARL* is the expected number of months to the first signal as follows

$$ARL(h, \rho_1) = \sum_{t=1}^{\infty} t\, \gamma(\tau, h, \rho_1). \tag{2.17}$$

Considering a fixed decision boundary [0, t*], a false alarm (α) is defined as the probability of a signal under H_0 by time t* in (2.18). After that, power $(1 - \beta)$ is determined as the probability of a signal under H_1 by time t* in (2.19) and power $(1 - \beta(\rho_g))$ as the probability of a signal under $\lambda_g N_i$ by time t* in (2.20).

$$\{P(t^*, h, \rho_1) \mid H_0\} = \alpha, \tag{2.18}$$

$$\{P(t^*, h, \rho_1) \mid H_1\} = (1 - \beta), \tag{2.19}$$

$$\{P(t^*, h, \rho_1) \mid \lambda_g N_i \text{ where } \lambda_g N_i \neq \lambda_1 N_i\} = (1 - \beta(\rho_g)). \tag{2.20}$$

The pair values of (ρ_1, h) is needed to choose, which makes the probability of a signal under H_0 by time t* reach the value of α. Under the chosen (ρ_1, h), the power $(1 - \beta)$ is assessed by obtaining the probability of a signal under H_1 by time t*. In this thesis, α is typically equal to 0.05. According to the traditional CUSUM, the performance of a monitoring scheme depends on the expected number of claims $\lambda_0 N_i$. Therefore H_0 for $\lambda_0 N_i$ is considered by assuming the number of units shipped being the same amount each month. The performance of a monitoring scheme for $\lambda_0 N_i$ = {0.34(0.0017×200), 5.0, 6.87(0.0055×1250) and 10} per unit per month is expected to be observed for detecting by time t*, where t* = {6, 12 and 24}. The choices of t* can have a significant effect on performance of a monitoring scheme. The selected values of

t^* here are based on the measurement period of a performance index (t^* = 6 and 12) and warranty period (t^* = 24), of which information is obtained from a certain company.

The calculation of signal probabilities is based on Markov chain approach. The CUSUM process is approximated by discretizing the increments $\widetilde{W} = W(t) - W(t-1)$. The $\widetilde{W}$ is divided into small value Δ and defines as:

$$\widetilde{W} = r\Delta \quad \text{if } (r-1)\Delta < \widetilde{W} \le r\Delta, \tag{2.21}$$

where r = {– (R–1), – (R–2),…, R–1, R}, and R is sufficiently large with negligible $Pr\{\widetilde{W} > R\Delta\}$. It is also defined as the discrete approximating CUSUM process with $\tilde{G}(0) = 0$ and

$$\tilde{G}(t) = \max(0, \tilde{G}(t-1) + \widetilde{W}). \tag{2.22}$$

The CUSUM can be considered as a random walk over state 0,1,…,Z where Z is absorbing state. A Markov chain is now considered for the process $\tilde{G}(t)$ and the state at time t is;

0 iff $\tilde{G}(t) = 0$,

r iff $\tilde{G}(t) = r\Delta$, r = {1,…, Y−1},

Z iff $\tilde{G}(t) \ge Z\Delta$.

To obtain signal probabilities, $X(t)$ is defined as state at time t where t = 0,1,2,…and let $p_{r,s}$ be transition probability of going from state r to state s. The transition probability matrix $Y(t)$ for the process at time t can be expressed as follows.

$$Y(t,r,s) = p_{r,s} = Pr(X(t) = s \mid X(t-1) = r), \tag{2.23}$$

where $r, s \in \{0,\dots,Z\}$ and $t = 1,2,\dots$

The transition probability matrix $Q(t)$ can be written as:

$$Y(t) = \begin{bmatrix} p_{0,0} & p_{0,1} & \cdots & p_{0,Z-1} & p_{0,Z} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ p_{Z-1,0} & p_{Z-1,1} & \cdots & p_{Z-1,Z-1} & p_{Z-1,Z} \\ p_{Z,0} & p_{Z,1} & \cdots & p_{Z,Z-1} & p_{Z,Z} \end{bmatrix}, \tag{2.24}$$

which

$$Y(t,Z,Z) = Pr(X(t) = Z \mid X(t-1) = Z) = 1, \tag{2.25}$$

$$Y(t,Z,s) = Pr(X(t) = s \mid X(t-1) = Z) = 0, \text{ where } s = 0,\dots, Z-1. \tag{2.26}$$

Thus (2.24) can be re-written as:

$$Y(t) = \begin{bmatrix} p_{0,0} & p_{0,1} & \cdots & p_{0,Z-1} & p_{0,Z} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ p_{Z-1,0} & p_{Z-1,1} & \cdots & p_{Z-1,Z-1} & p_{Z-1,Z} \\ 0 & 0 & \cdots & 0 & 1 \end{bmatrix}. \tag{2.27}$$

For $r = \{0, \ldots, Z-1\}$,

$Y(t,r,0) = Pr(X(t) = 0 \mid X(t-1) = r)$,

$= Pr(\tilde{G}(t)$ decreases at least $r\Delta$),

$= Pr(\tilde{G}(t) \leq -r\Delta)$. (2.28)

For $r = \{0, \ldots, Z-1\}$, $s = \{1, \ldots, Z-1\}$,

$Y(t,r,s) = Pr(X(t) = s \mid X(t-1) = r)$,

$= Pr(\tilde{G}(t)$ changes equal to $(s-r)\Delta$),

$= Pr(\tilde{G}(t) = (s-r)\Delta)$,

$= Pr((s-r-1)\Delta < \tilde{G}(t) \leq (s-r)\Delta)$. (2.29)

For $r = \{0, \ldots, Z-1\}$,

$Y(t,r,Z) = Pr(X(t) = Z \mid X(t-1) = r)$,

$= Pr(\tilde{G}(t)$ increases at least $Z - r$),

$= 1 - \sum_{s=0}^{Z-1} Pr(X(t) = s \mid X(t-1) = r)$,

$= 1 - \{Pr(\tilde{G}(t) \leq (Z-1-r)\Delta\}$. (2.30)

Starting from $t = 0$, the probabilities that a signal occurs by time t is

$$Y(t,0,Z) = Pr(X(t) = Z \mid X(0) = 0). \tag{2.31}$$

Thus, $P(t,h,\rho_1)$ in (2.15) can be expressed as:

$$P(t,h,\rho_1) = Z(t,0,Z),\ t = 1,2,\ldots \tag{2.32}$$

2.3 The difference of CUSUM design approach between this thesis and Lawless et al. (2012)

Table 2.2 Summary of CUSUM design parameters proposed in this thesis and Lawless et al. (2012)

Column		1	2
CUSUM design parameters		This thesis	Lawless et al.(2012)
1	$\lambda_0 N_i$	**varied**	fixed
2	$\lambda_g N_i$	**varied**	**varied**
3	I	**varied**	fixed
4	(ρ_1, h)	**varied**	fixed

The proposed CUSUM for drawing out a scheme of detection in claim management is an application of CUSUM proposed by Lawless et al. (2012).

Lawless et al. (2012) did neither investigate nor provide CUSUM design parameters regarding $\lambda_0 N_i$, $I(I \geq 1)$ and (ρ_1, h) except $\lambda_g N_i$. CUSUM design approach in their proposal was not well appropriate for easily drawing out a scheme of detection. Therefore, it should be developed. In Section 2.5, the above mentioned CUSUM design parameters are investigated and provided in Appendix A. As a result, the CUSUM design approach which covers a wide range of expected number of claims per month and various numbers of months for which units have been shipped is easily performed.

2.4 Shewhart procedures

Shewhart u-chart is applied for a comparative analysis in Section 2.6 which is based on new claims and new units generated over time. Total number of claims in observation time t (n_t) in $\widetilde{N}$ is used, then $\hat{\lambda}_t$ can be calculated by (2.2) for monitoring in the control chart. $\hat{\lambda}_t$ is monitored until it crosses over a fixed upper control limit UCL_t which indicates that the number of claims is out of control.

Upper control limit by time t, (UCL_t), can be written in (2.33) by assuming that λ_0 is given,

$$\text{UCL}_t = \lambda_0 + c\sqrt{\frac{\lambda_0}{\tilde{N}}}\text{, where } c > 0. \tag{2.33}$$

CUSUM and Shewhart procedures are different. As shown in (2.4), a decision regarding whether or not the number of claims is in-control in CUSUM statistics is based on likelihood ratio statistics (2.12) which are the cumulative sums of the deviations of the number of claims from a target value. It differs from the Shewhart procedures using individual observation, i.e, $\hat{\lambda}_t$.

In order to assess the properties between these two procedures, the pair values of (ρ_1, h) is selected for CUSUM and the c value is selected for Shewhart which will provide the same in-control *ARL* (ARL_0). Under out-of-control situations as well as an increase of the number of claims, the out-of-control *ARL* (ARL_g) in each procedure is compared. *ARL* in CUSUM and in Shewhart is determined by using simulation.

2.5 Properties of CUSUM procedures

General properties of CUSUM are investigated for their applicability to a general business. In this section, the properties of proposed statistical methods, for a specific value of $\lambda_0 N_i$ = 6.87, various values of (ρ_1, h) and t^* are discussed. In subsection 2.4.1, probabilities of a signal under H_0 ($\lambda_0 N_i$) are considered under the restriction on a fixed α. In subsection 2.4.2, probabilities of a signal under H_1 are observed and in subsection 2.4.3, probabilities of a signal under $\lambda_g N_i$ where $\lambda_g N_i \neq \lambda_1 N_i$ are examined.

2.5.1 Probability of a signal under H_0

Fig. 2.1 shows the probability of a signal under H_0 ($\lambda_0 N_i$ = 6.87) for values of (ρ_1, h) and t^* =12. It shows that threshold h is smaller if ρ_1 is larger. The larger value of ρ_1 provides the smoother curve which indicates the lower probability of a signal by time t. Compared to Fig.2.1 and Fig.2.2, threshold h in Fig.2.2 is required the larger value to provide α equal to 0.05 than that for t^* =12 in Fig.2.1. Consequently, the curves are smoother compare to that for t^* =12 in Fig. 2.1.

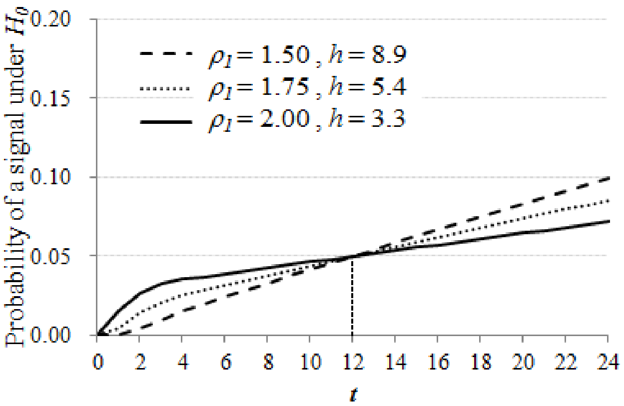

Figure 2.1 Probability of a signal under H_0 for values (ρ_1, h), $\lambda_0 N_i$= 6.87, t^* =12

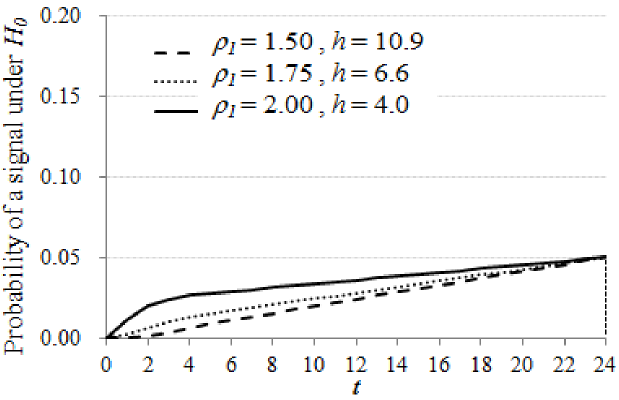

Figure 2.2 Probability of a signal under H_0 for values (ρ_1, h), $\lambda_0 N_i$= 6.87, t^* =24

2.5.2 Probability of a signal under H_1

In Fig. 2.3 and 2.4, the same values of (ρ_1, h) as shown in Fig.2.1 and Fig. 2.2 are used respectively to assess powers and general trends of signal probabilities under H_1. A general trend is that the larger value of ρ_1 provides the steeper curve. In the case of the longer t^*, like Fig.2.4, it makes steeper curve than that of Fig.2.3 at the same value of ρ_1. However, at the same value of $\alpha = 0.05$ for $t^* = 12$ and for $t^* = 24$, Fig.2.3 and 2.4 present an identical power value of 1.00 for all values of ρ_1.

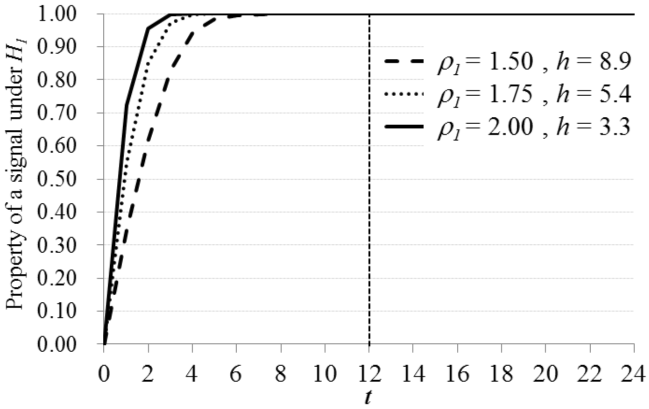

Figure 2.3 Probability of a signal under H_1 for values (ρ_1, h), $\lambda_0 N_i$=6.87, t^* =12, α = 0.05

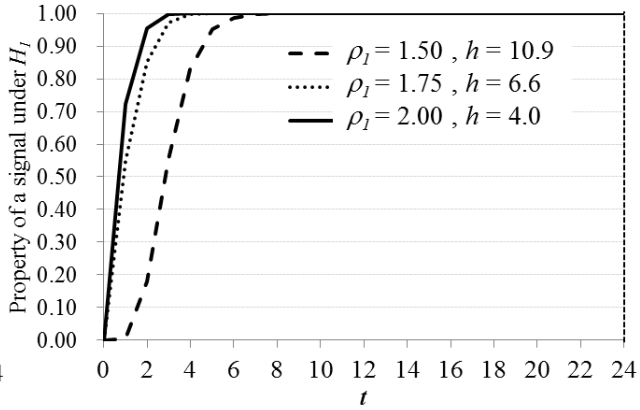

Figure 2.4 Probability of a signal under H_1 for values (ρ_1, h), $\lambda_0 N_i$=6.87, t^* =24, α = 0.05

2.5.3 Probability of a signal under $\lambda_g N_i$ where $\lambda_g N_i \neq \lambda_1 N_i$

In Fig. 2.5 and 2.7, the same values of (ρ_1, h) as shown in Fig.2.1 are used to assess powers and general trends of signal probabilities under $\lambda_g N_i$ = 8.59 and 10.31 respectively. The larger $\lambda_g N_i$ like Fig.2.7 makes a steeper curve and higher power. In Fig. 2.7, the powers of (ρ_1, h) for t^* =12 reach about 1.00. In Fig. 2.6 and 2.8, the same values of (ρ_1, h) as shown in Fig.2.2 are used. In Fig. 2.6 for $\lambda_g N_i$ = 8.59, each power for t^* = 24 corresponding to ρ_1 = 1.50, 1.75 and 2.00 represents 0.984, 0.904 and 0.802 respectively which is smaller than that for $\lambda_g N_i$ = 10.3 in Fig. 2.8. The smaller value of ρ_1 and the higher value of $\lambda_g N_i$ make a steeper curve and higher power.

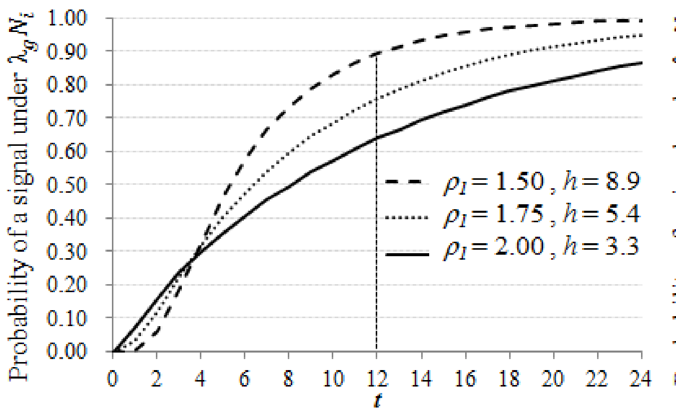

Figure 2.5 Probability of a signal under $\lambda_g N_i$ = 8.59 for values (ρ_1, h), $\lambda_0 N_i$=6.87, t^* =12, α = 0.05

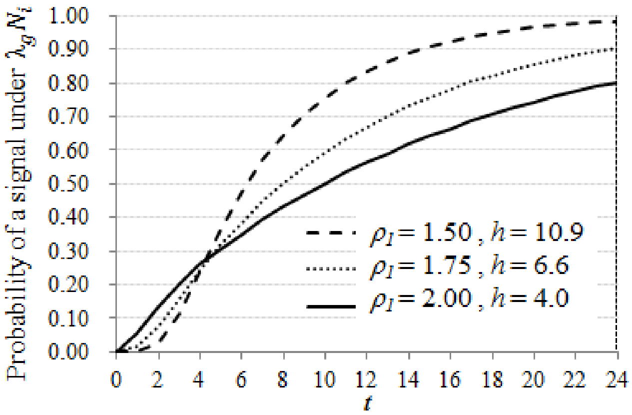

Figure 2.6 Probability of a signal under $\lambda_g N_i$ = 8.59 for values (ρ_1, h), $\lambda_0 N_i$=6.87, t^* =24, α = 0.05

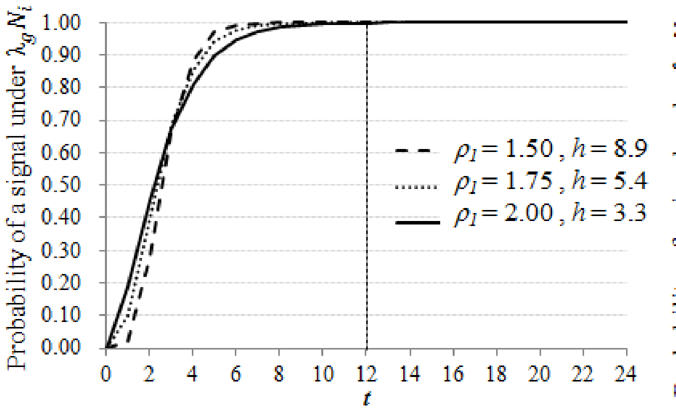

Figure 2.7 Probability of a signal under $\lambda_g N_i$ = 10.31 for values (ρ_1, h), $\lambda_0 N_i$=6.87, t^* =12, α = 0.05

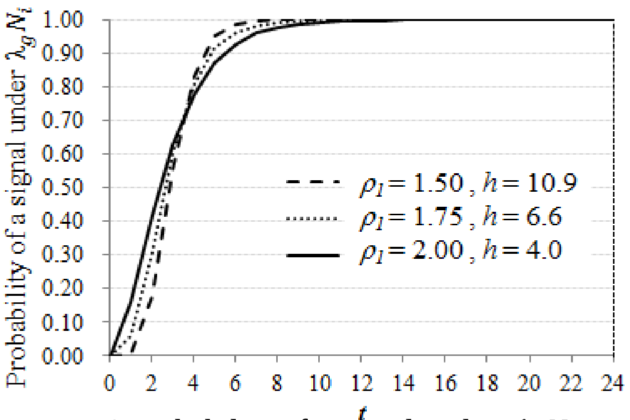

Figure 2.8 Probability of a signal under $\lambda_g N_i$ = 10.31 for values (ρ_1, h), $\lambda_0 N_i$=6.87, t^* =24, α = 0.05

From sections 2.4.1 and 2.4.3, the general trend is that a large value of ρ_1 favors the null (in-control) hypothesis (see Fig.2.1 and 2.2), whereas a small value of ρ_1 favors the alternative (out of control) hypothesis (see Fig. 2.5 – 2.8). When one combination of (ρ_1, h) is chosen for monitoring scheme, it is obviously recognized that the probability of a signal should to be low under H_0 and to be high under $\lambda_g N_i \neq \lambda_1 N_i$. In this way, using entire probabilities of a signal under H_0 and $\lambda_g N_i \neq \lambda_1 N_i$ seems more informative than relying solely on α and $(1-\beta(g))$. ARL_0 is used to represent for ARL under H_0 and use ARL_g to represent for ARL under $\lambda_g N_i$ when $\lambda_g N_i \neq \lambda_1 N_i$. Table 2.3 indicates the ARL_0, ARL_g corresponding (ρ_1, h), α = 0.05, t^* = 12 and 24 for $\lambda_0 N_i$ = 6.87, I = 5 and $\lambda_g N_i$ = 8.59, 10.31. It provides the same values α for each t^*, however, ARL_0 is a different value and considerably longer if t^* is larger. ARL_0 is longer as ρ_1 is larger. However, ARL_g is shorter as $\lambda_g N_i$ is larger and the smaller value ρ_1 has much shorter ARL_g than that of the larger value. According to the value of ARL_0 and ARL_g in Table 2.3, the probabilities of a signal under H_0 as shown in Fig. 2.1-2.2 and under $\lambda_g N_i \neq \lambda_1 N_i$ as shown in Fig. 2.5-2.8 for various values of (ρ_1, h) show the different performances.

Table 2.3 ARL_0 and ARL_g corresponding (ρ_1,h), $(1-\beta(g))$ and $t^* =$ 12 and 24 for $\lambda_0 N_i$ = 6.87, I = 5, $\lambda_g N_i$ = 8.59 and 10.31

t^*	ρ_1	h	$\lambda_0 N_i$ = 6.87		$\lambda_g N_i$= 8.59 (ρ_g = 1.25)		$\lambda_g N_i$ = 10.31 (ρ_g = 1.50)	
			α	ARL_0	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g
12	1.50	8.9	0.05	226.8	0.894	7.0	1.000	3.2
	1.75	5.4	0.05	311.9	0.758	9.2	1.000	3.1
	2.00	3.3	0.05	507.0	0.638	12.4	0.999	3.1
24	1.50	10.9	0.05	458.3	0.984	8.2	1.000	3.5
	1.75	6.6	0.05	537.4	0.904	11.5	1.000	3.4
	2.00	4.0	0.05	805.5	0.802	15.2	1.000	3.3

For detection of a major quality problem (MQP) for any particular $\lambda_0 N_i$, a choice of (ρ_1, h) should be selected which provides some suitable values of $(1-\beta(g))$, ARL_0 and ARL_g corresponding to α, t^* for $\lambda_0 N_i$ and $\lambda_g N_i$. Using these results, the analysis of Example I and II is presented in Section 4.1. ARL_0 and ARL_g corresponding (ρ_1, h) are provided, α = 0.05, $(1-\beta(g))$, t^* and $\lambda_g N_i$ (ρ_g) for $\lambda_0 N_i$ and I as indicated in Appendix A for designing a CUSUM chart. These values are calculated as outlined in Section 2.2.2 by applying R code. As for many electronic appliances such as computer, digital camera and smart phone, a new model will be released every 6 or 12 months, therefore the value of I could be fixed at some specific period as mentioned above. On the other hand, the value of t^* should be longer than that of I. Therefore, the values of $I \leq 6$ are used and tables for designing CUSUM are prepared in Appendix A.

2.6 Comparatives analysis between CUSUM and Shewhart procedures

To compare these two procedures, the design parameters for each procedure (c for Shewhart procedures and (ρ_1, h) for CUSUM procedures) were chosen so as to have approximately the same in-control average run length (ARL_0). The in-control ARL_0 of 205.0 is selected for two procedures. The simulation result of ARLs at various values of ρ_g is shown in Table 2.4. As a result, CUSUM is faster to detect the increase in number of claims for $\rho_g > 1$ comparing to Shewhart. For $\rho_g = 1.25$, CUSUM gives about 16. As a result, CUSUM shows about two times faster than that of Shewhart.

Table 2.4 ARL_g values corresponding to ARL_0 = 205.0 for $\lambda_0 N_i$ = 6.87, I =1 and ρ_g = {1.25, 1.50, 1.75 and 2.00} for both Shewhart and CUSUM procedures

ρ_g	Shewhart	CUSUM
	c = 3.0	**ρ_1 = 1.5**
		h = 8.7
1.25	33.6	15.8
1.50	9.9	5.5
1.75	4.3	3.3
2.00	2.5	2.4

The comparative analysis between two procedures based on the probability of a signal by time t^* = 12 is shown here. The design parameters for each procedure (c for Shewhart procedures and (ρ_1, h) for CUSUM procedures) were chosen so as to have approximately the same value of α. Then, the values of $(1-\beta(g))$ are compared. Fig. 2.9 shows the probability of a signal under H_0 ($\lambda_0 N_i$ = 6.87) for Shewhart and CUSUM procedures. The α = 0.058 by time t^* = 12 is selected for two procedures.

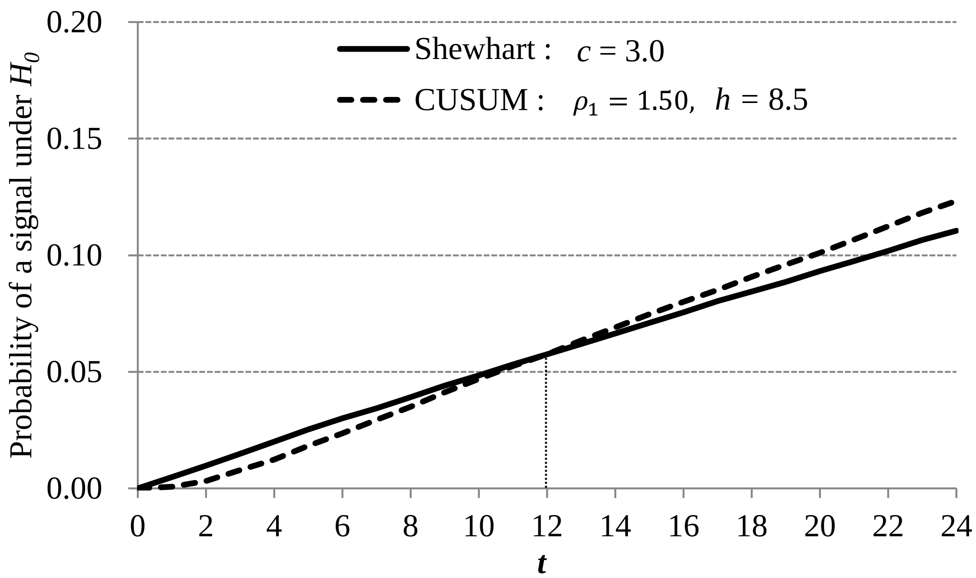

Figure 2.9 Probability of a signal under H_0 for Shewhart and CUSUM procedures, $\lambda_0 N_i$= 6.87, t* =12

In Fig. 2.10 and 2.11, the same values of c = 3.0 for Shewhart procedures and ($\rho_1 = 1.50, h$ = 8.5) for CUSUM procedures as shown in Fig.2.9 are used to assess powers and general trends of signal probabilities under $\lambda_g N_i$ = 8.59 and 10.31 respectively.

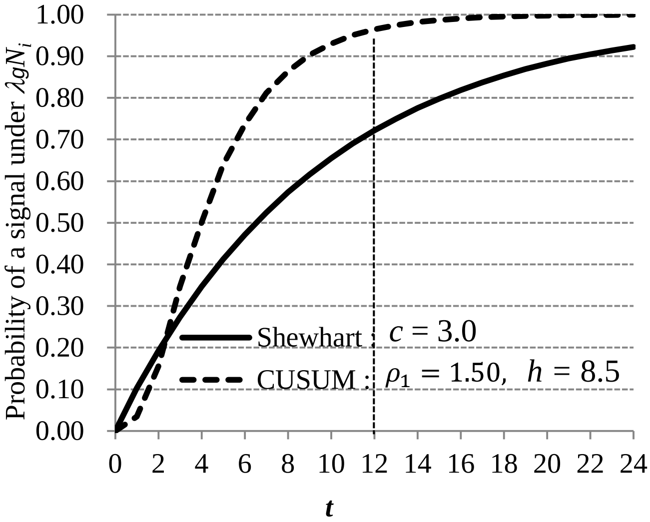

Figure 2.10 Probability of a signal under $\lambda_g N_i$ = 8.59 for Shewhart and CUSUM procedures, $\lambda_0 N_i$=6.87, t* =12, α = 0.058

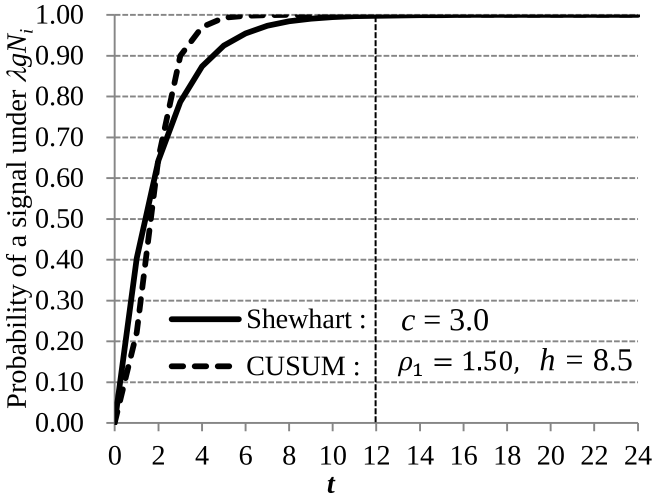

Figure 2.11 Probability of a signal under $\lambda_g N_i$= 10.31 for Shewhart and CUSUM procedures, $\lambda_0 N_i$=6.87, t* =24, α = 0.058

A general trend is that Shewhart has slightly higher power for the first two months, however, CUSUM passes Shewhart after two months and rapidly increases. As a result, CUSUM provides the power of 0.96 by t* =12 for $\lambda_g N_i$ = 8.59 (see Fig. 2.10) and achieves the ideal power by t* =12 for $\lambda_g N_i$ = 10.31 (see Fig. 2.11).

Chapter 3

Statistics for examining effectiveness of actions taken

Overview

When a major quality problem is detected, the monthly claims are aggregated at specific time intervals for creating QCMM. In order to examine the effectiveness of the actions taken and identify the actions needed to improve the claim management process, the proposed method requires claim data over certain intervals for the analysis.

This chapter describes the method of analyzing grouped claims data for examining effectiveness of actions taken. Section 3.1 introduces a model of grouped claim data over time intervals. Section 3.2 provides an estimation of effectiveness of actions taken. Section 3.3 and 3.4 provide hypothesis settings and likelihood ratio statistic. Then the properties of the proposed method are discussed in Section 3.5. Section 3.6 shows comparative analysis between the previous research and the proposed method.

3.1 Model of grouped claim data over time intervals

k : index denoting time interval, $k \in \{1,2,3\}$

l : index denoting product shipment interval, $l \in \{1,2,3\}$

Q_k : specific time interval; $\bar{Q}_k$, for its length

M_l : number of units shipped in Q_l

$\mu_{l,k}$: expected claim rate in Q_k on units shipped in Q_l

$m_{l,k}$: number of claims in Q_k on units shipped in Q_l

u : effective stop usage rate ($0 \le u \le 1$ where u = 1.0 is the maximum value)

v : effective stop shipment rate ($0 \le v \le 1$ where v = 1.0 is the maximum value)

q : effective recurrence prevention rate ($0 \le q \le 1$ where q = 1.0 is the maximum value)

Based on the structure of QCMM in Table 1.1, six regions are defined as shown in

Table 3.1. The [*l*, *k*] notation is used to specify the matrix region: the *l* for the shipment interval, and *k* for the claim occurrence interval. For example, region [1,2] indicates that claim data grouped in a specific time interval Q_2 for units shipped in Q_1.

In Table 3.1, region [1,1] indicates the grouped claims before MQPR. After MQPR is identified, actions taken in regions [1,2] and [2,2] should be examined. After RPC is determined, actions taken in regions [1,3],[2,3] and [3,3] should be examined. This thesis is assumed that claim do not recur therefore no further actions are taken after RCO. Actions taken are classified into two types: one of them, directly affecting the number of units shipped (N_i) such as stop usage, stop shipment, and the other, one directly affect the claim rate ($\mu_{l,k}$) such as recurrence prevention by replacement nonconformance products with newly designed products. A particular action is assumed to be taken for claims in each region. For region [1,2], "stop usage" is taken. The effectiveness of the actions taken is represented by using the effective stop usage rate, *u*. For region [2,2], "stop shipment" is taken. The effectiveness of the actions taken is represented by using the effective stop shipment rate, *v*. For region [3,3], the effectiveness of the actions taken is represented by using the effective recurrence prevention rate, *q*. For region [1,3], it has a combination of "stop usage" and "recurrence prevention". The effectiveness of the actions taken is represented by using *u* and *q*. For region [2,3], it has a combination of "stop shipment and "recurrence prevention". The effectiveness of the actions taken is represented by using *v* and *q*.

Table 3.1 Structure for grouping claim data by the length of time intervals $\bar{Q}_1, \bar{Q}_2$ and $\bar{Q}_3$

<table>
<tr><td colspan="3"></td><td colspan="2">$\bar{Q}_1$</td><td>$\bar{Q}_2$</td><td colspan="2">$\bar{Q}_3$</td></tr>
<tr><td colspan="2" rowspan="2"></td><td rowspan="2">No. of units shipped in Q_l (M_l)</td><td colspan="5">Time of claim occurrence</td></tr>
<tr><td>P1: MR – FCO</td><td>P2: FCO – MQPR</td><td>P3: MQPR – RPC</td><td>P4: RPC – RCO</td><td>P5: RCO</td></tr>
<tr><td rowspan="5">Time of product shipment</td><td>P1: MR – FCO</td><td rowspan="2">M_1</td><td colspan="2">[1,1] $m_{1,1}$, $\mu_{1,1}$,</td><td rowspan="2">[1,2] $m_{1,2}$, $\mu_{1,2}$, u</td><td colspan="2" rowspan="2">[1,3] $m_{1,3}$, $\mu_{1,3}$, u,q</td></tr>
<tr><td>P2: FCO – MQPR</td><td></td><td></td></tr>
<tr><td>P3: MQPR – RPC</td><td>M_2</td><td></td><td></td><td>[2,2] $m_{1,2}$, $\mu_{2,2}$, v</td><td colspan="2">[2,3] $m_{2,3}$, $\mu_{2,3}$, v,q</td></tr>
<tr><td>P4: RPC – RCO</td><td rowspan="2">M_3</td><td></td><td></td><td></td><td colspan="2" rowspan="2">[3,3] $m_{3,3}$, $\mu_{3,3}$, q</td></tr>
<tr><td>P5: RCO</td><td></td><td></td><td></td></tr>
</table>

The number of units shipped (M_l), the number of claims ($m_{l,k}$), and the expected claim rates $\mu_{l,k}$ corresponding to the three intervals in Table 3.1 are expressed as follows; the number of units shipped in Q_l is the subtotal $M_l = \sum_{i \in Q_l} N_i$. The number of claims in Q_k for units shipped in Q_l is the subtotal

$$m_{l,k} = \sum_{i \in Q_l} \sum_{a \in Q_k} n_{i,a} \,. \tag{3.1}$$

By referring to Table 2.1 and (2.1), the log likelihood of a Poisson process with rate function λN_i over the number of claims in Q_k for units shipped in Q_l can be represented by formula (3.2)

$$logL([l,k],\lambda) = -\sum_{i \in Q_l} \sum_{a \in Q_k} \lambda N_i + \sum_{i \in Q_l} \sum_{a \in Q_k} n_{i,a} \log(\lambda N_i), \tag{3.2}$$

which gives an estimate of the expected claim rate $\mu_{l,k}$ in Q_k for units shipped in Q_l and is represented by formula (3.3)

$$\hat{\mu}_{l,k} = \frac{\sum_{i \in Q_l} \sum_{a \in Q_k} \hat{\lambda} N_i}{M_l}. \tag{3.3}$$

Note: λ_a is constant (λ).

By referring to Table 3.1, the log likelihood function of a Poisson process with rate function $\mu_{l,k}$ over the number of claims in Q_k for units shipped in Q_l is represented by formula (3.4)

$$logL\left([l,k],\mu_{l,k}\right) = -M_l \mu_{l,k} + m_{l,k} \log\left(M_l \mu_{l,k}\right), \tag{3.4}$$

which gives an estimate of the expected claim rate in Q_k for the units shipped in Q_l and is represented by formula (3.5)

$$\hat{\mu}_{l,k} = m_{l,k}/M_l. \tag{3.5}$$

The sum of independent Poisson random variables is also Poisson, which is a useful property of a Poisson distribution. This means that claim data in Table 2.1 can be used to estimate expected claim rate ($\hat{\mu}_{l,k}$) by using (3.2) as shown in (3.3), or claim data in Table 3.1 can also be used to estimate expected claim rate ($\hat{\mu}_{l,k}$) by using (3.4) as shown in (3.5).

3.2 Estimation of effectiveness of actions taken

The effectiveness of actions taken in region [1,2],[2,2],[3,3],[1,3] and [2,3] in Table 3.1 is estimated by the proportion of expected claim rate before actions taken in region [1,1] and after actions taken in regions [1,2],[2,2],[3,3],[1,3] and [2,3]. This thesis gives an estimate of the effective rate in the above region as expressed in (3.6) – (3.10) respectively.

Region [1,2]: The effective stop usage rate,

$$\hat{u} = \frac{\hat{\mu}_{1,1} - \hat{\mu}_{1,2}}{\hat{\mu}_{1,1}} . \tag{3.6}$$

Region [2,2]: The effective stop shipment rate,

$$\hat{v} = \frac{\hat{\mu}_{1,1} - \hat{\mu}_{2,2}}{\hat{\mu}_{1,1}} . \tag{3.7}$$

Region [3,3]: The effective stop shipment rate,

$$\hat{q} = \frac{\hat{\mu}_{1,1} - \hat{\mu}_{3,3}}{\hat{\mu}_{1,1}} . \tag{3.8}$$

Region [1,3]: The combination of the effective stop usage rate and the effective recurrence prevention rate,

$$\hat{u}, \hat{q} = \frac{\hat{\mu}_{1,1} - \hat{\mu}_{1,3}}{\hat{\mu}_{1,1}} . \tag{3.9}$$

Region [2,3]:The combination of the effective stop shipment rate and the effective recurrence prevention rate,

$$\hat{v}, \hat{q} = \frac{\hat{\mu}_{1,1} - \hat{\mu}_{2,3}}{\hat{\mu}_{1,1}} . \tag{3.10}$$

3.3 Hypothesis testing

The null and alternative hypotheses for each region indicated in Table 3.1 are stated as follows. If u, v, and q = 0, the action has zero effectiveness. If $u > 0$, $v > 0$, and/or $q > 0$, the action taken has some degree of effectiveness. If u, v, and q = 1, the action taken is completely effective. In other word, there are no claims. The hypothesis settings for testing are given by (3.11), (3.13), (3.15), (3.17) and (3.19). The likelihood function for the null hypothesis is given by (3.4). The likelihood functions for the alternative hypotheses are given by (3.12), (3.14), (3.16), (3.18) and (3.20).

Alternative hypotheses (3.11) and (3.13) respectively give the effective stop usage rate, u, and the effective stop shipment rate, v. They are used for testing the effectiveness of stopping usage of units shipped before MQPR in region [1,2] and the effectiveness of stopping shipment after MQPR in region [2,2]. The effective stop usage rate u and effective stop shipment rate v directly affect the number of units shipped (N_i) where u and v can be outlined in (3.12) and (3.14).

Region [1,2]:

$$H_0: u = 0; \;\; H_1: u > 0, \tag{3.11}$$

$$log\ L([1,2], H_1) = -(1-u)M_1\mu_{1,2} + m_{1,2}\log\Big((1-u)M_1\mu_{1,2}\Big), \tag{3.12}$$

Region [2,2]:

$$H_0: v = 0; \;\; H_1: v > 0, \tag{3.13}$$

$$logL([2,2], H_1) = -(1-v)M_2\mu_{2,2} + m_{2,2}\log\Big((1-v)M_2\mu_{2,2}\Big), \tag{3.14}$$

Region [3,3]:

$$H_0: q = 0; \;\; H_1: q > 0 \tag{3.15}$$

$$logL([3,3], H_1) = -M_3(1-q)\mu_{3,3} + m_{3,3}\log\Big(M_3(1-q)\mu_{3,3}\Big), \tag{3.16}$$

Region [1,3]:

$$H_0: u = 0, q = 0; \;\; H_1: u > 0, q > 0, \tag{3.17}$$

$$logL([1,3], H_1) \tag{3.18}$$

$$= -(1-u)M_1(1-q)\mu_{1,3} + m_{1,3}\log\Big((1-u)M_1(1-q)\mu_{1,3,}\Big)$$

Region [2,3]:

H_0: $v = 0$, $q = 0$; H_1: $v > 0$, $q > 0$,   (3.19)

$logL([2,3], H_1)$ (3.20)

$$= -(1-v)M_2(1-q)\mu_{2,3} + m_{2,3}\log\left((1-v)M_2(1-u)\mu_{2,3}\right).$$

An alternative hypothesis (3.15) gives the effective recurrence prevention rate q. It is used for testing the effectiveness of the recurrence prevention measures that are taken for units shipped after RPC in region [3,3]. The effective recurrence prevention rate q directly affects the claim rate ($\mu_{l,k}$) because the recurrence prevention is performed to eliminate the root cause of the problem. The effective recurrence prevention rate q can be outlined in (3.16).

The alternative hypothesis that is given by (3.17) represents the combination of the effective stop usage rate, u and the effective recurrence prevention rate, q. It is used for testing the effectiveness of action taken in region [1,3], where u and q can be outlined in (3.18). The alternative hypothesis that is given by (3.19) represents the combination of the effective stop shipment rate v and the effective recurrence prevention rate, q. It is used for testing the effectiveness of action taken in region [2,3], where v and q can be outlined in (3.20).

3.4 Likelihood ratio (LR) statistic for testing

The likelihood ratio statistic is expressed in (3.21).

$$\text{LR} = -2\left(\frac{logL(H_0)}{logL([l,k], H_1)}\right). \tag{3.21}$$

The definition of (3.21) is outlined as follows;

1) $logL(H_0)$ is denoted as the maximum of the likelihood function when u, v and q are in a null parameter space. Here, a specific number of claims (λN_i) is specified for the null parameter.

2) $logL([l,k], H_1)$ is denoted as the maximum of the likelihood function when u, v and q are in an alternative parameter space. For the alternative parameter, the values of $\mu_{l,k}$ and u, v and q are needed to estimate. This thesis used the maximum likelihood as a method of estimating $\mu_{l,k}$ which its formula is shown in (3.5). Estimated formulas for u, v and q are shown in (3.6) - (3.10).

The LR statistic is assumed to distribute as a Chi-squared random variable with degrees of freedom equal to the difference in the number of parameters between two likelihood functions. For testing the null hypothesis against the alternative hypothesis, a critical region is selected for testing so that the test has a desired significant level α = 0.05. If LR statistic is greater than the critical region, the test rejects null hypothesis under the null hypothesis being true. Then, $(1-\beta)$ is taken as the power of the LR test and used for representing the result of testing. The power value of $(1-\beta)$ indicates the probability of rejecting null hypothesis under alternative hypothesis being false. Generally, α should be kept as low as possible in order to avoid unjustified actions and/or disrupt operations looking for nonexistent special causes. On the other hand, $(1-\beta)$ should be kept as high as possible in order to quick implement actions needed and prevent substantial number of claims.

In this thesis, λN_i is assumed to be the normal number of claims specified by a company or estimated on the basis of the past experience claim data on the same cause of quality problems. To investigate properties of the proposed method, a Poisson random variable with a specific number of claims (λN_i) is generated by using Mersenne-Twister random number generator. 50,000 LR simulations test are run by using the likelihood function for the null (3.4) and alternative (3.12), (3.14), (3.16), (3.18) and (3.20) hypothesis forms.

3.5 Properties of the proposed method

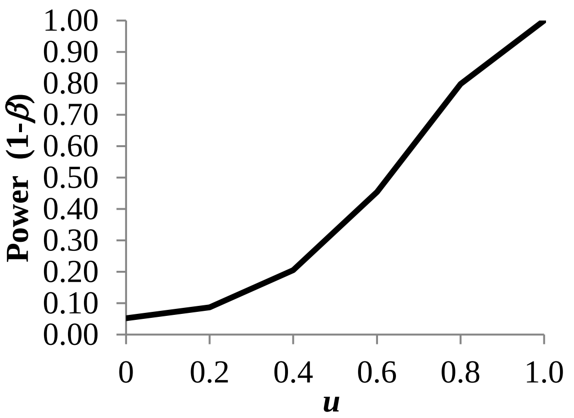

Figure 3.1 Power curve for u in region [1,2] for λN_i = 0.34 for α =0.05 and $\bar{Q}_1$ and $\bar{Q}_2$= 6

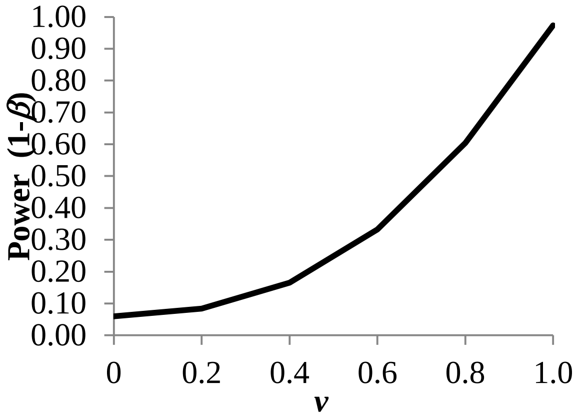

Figure 3.2 Power for v in region [2,2] for λN_i = 0.34 for α =0.05 and $\bar{Q}_2$ = 6

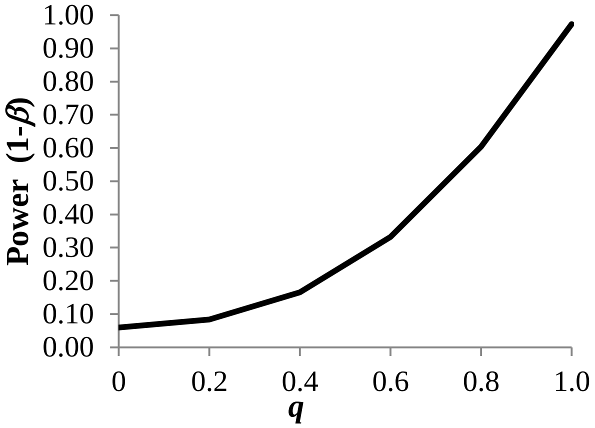

Figure 3.3 Power curve for q in region [3,3] for λN_i = 0.34 for α =0.05 and $\bar{Q}_3$= 6

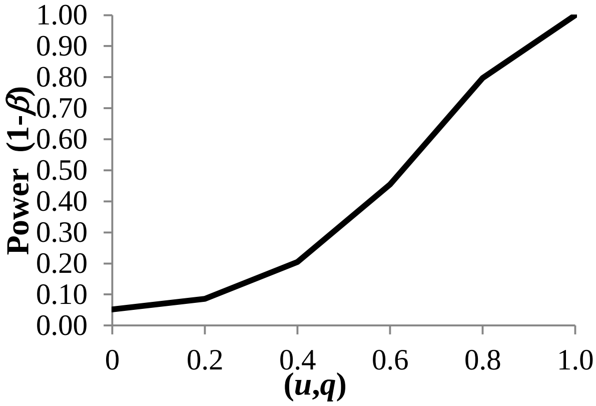

Figure 3.4 Power curve for u,q in region [1,3] for λN_i = 0.34 for α =0.05 and $\bar{Q}_1$and $\bar{Q}_3$= 6

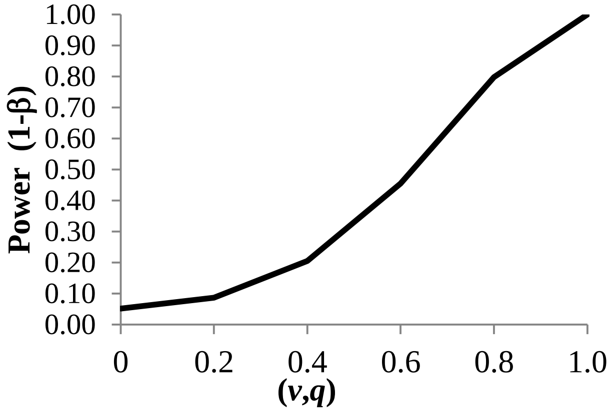

Figure 3.5 Power curve for v,q in region [2,3] for λN_i = 0.34 for α =0.05 and $\bar{Q}_2$ and $\bar{Q}_3$= 6

A preliminary investigation of the method for testing the effectiveness of the actions taken for a specific λN_i = 0.34 is performed under the assumption that length of time intervals $\bar{Q}_1, \bar{Q}_2$ and $\bar{Q}_3$ has an identical value. Therefore, a specific time interval $\bar{Q}_1, \bar{Q}_2$ and $\bar{Q}_3$= 6 is assumed for the analysis. Figure 3.1 – 3.5 plot the power curves for u in region [1,2],v in region [2,2], q in region [3,3],(u, q) in region [1,3] and (v, q) in region [2,3],which range from 0 to 1.0 respectively. Generally, the power value becomes better if the value of u, v, q, (u, q) and (v, q) is higher. As shown in Figure 3.2 and 3.3, the power curves in regions [2,2] and [3,3] were the same. In addition, Figure 3.1, 3.3 and 3.5 showed that the power curves in regions [1,2], [1,3], and [2,3] were the same. The reason is because these regions have an identical expected claim rate. The further analysis of regions [1,2] and [3,3] are focused on.

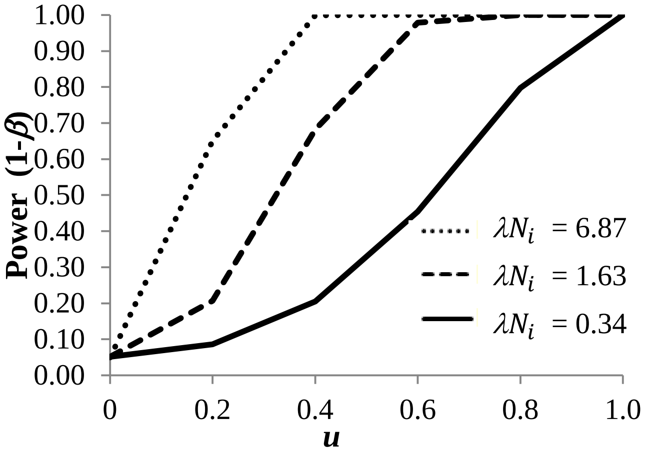

Figure 3.6 Power curves for λN_i = 0.34, 1.63, and 6.87 for α =0.05 and $\bar{Q}_1$ and $\bar{Q}_2$= 6

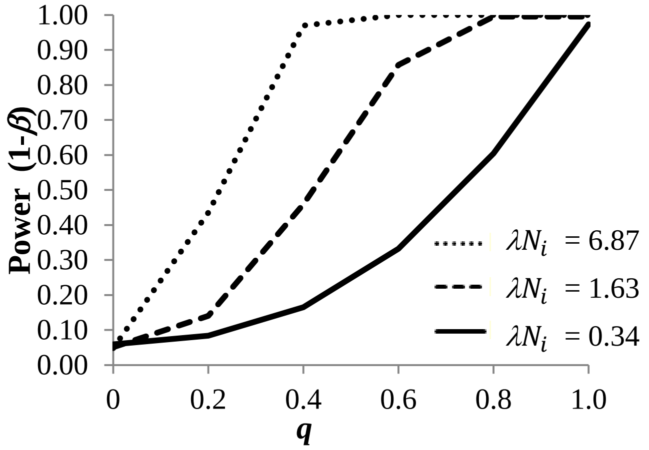

Figure 3.7 Power curves for λN_i = 0.34, 1.63, and 6.87 for α =0.05 and $\bar{Q}_3$ = 6

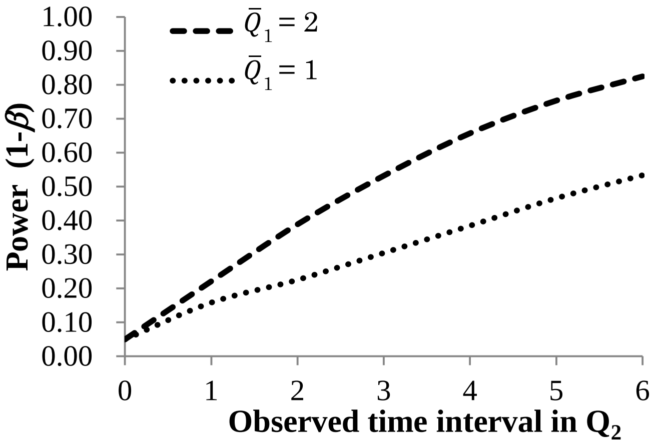

Figure 3.8 Power curves for λN_i = 0.34 for $\bar{Q}_1 = \{1,2\}$ and Q_2 for *u* =0.4 for α =0.05

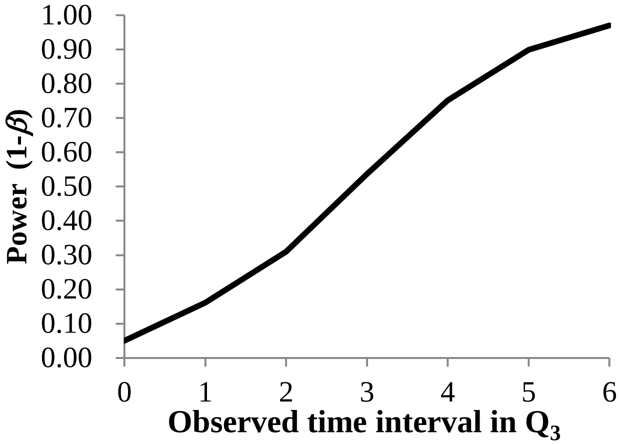

Figure 3.9 Power curve for λN_i = 0.34 for Q_3 for *q* = 0.4 for α =0.05

The power curves for regions [1,2] and [3,3] are related to the effective stop usage rate *u* and effective recurrence prevention rate *q*, respectively. Fig. 3.6 plots the power curves for *u* for $\bar{Q}_1$ and $\bar{Q}_2$ equal to 6 months. Fig. 3.7 plot the power curves for *q* for $\bar{Q}_3$ equal to 6 months. Basically, the larger the effective *u* and *q* rates, the greater the power. Moreover, the higher the number of claims per month, the greater the power, especially for λN_i= 6.87, which shows a high power $(1-\beta)$ = 1.0 for *u* = 0.4 and $(1-\beta)$ = 0.97 for *q* = 0.4. When *u* and *q* were the same value, the power of the effective stop usage rate *u* was greater than that of the effective stop recurrence rate *q* because region [1,2] had a larger expected claim rate than that of region [3,3].

Fig. 3.8 plots the power curves for $\bar{Q}_1 = \{1,2\}$, and Q_2, and Fig. 3.9 plots the power curve for Q_3. Basically, the longer the interval is , the higher the power becomes, which means that $\bar{Q}_1$ and $\bar{Q}_2$ need to be specified referring to the power in region [1,2]. $\bar{Q}_1$ and $\bar{Q}_3$ need to be specified referring to the power in region [1,3], and $\bar{Q}_2$ and $\bar{Q}_3$ need to be specified referring to the power in region [2,3]. $\bar{Q}_2$ needs to be specified referring to the power in region [2,2] and $\bar{Q}_3$ needs to be specified referring to the power in region [3,3].

As a result, λN_i, u, q, $\bar{Q}_1$, $\bar{Q}_2$, and $\bar{Q}_3$ have a significant effect on the power. By knowing the key parameters for testing effectiveness of the actions taken in the form of QCMM, they are important parameters for examining a particular λN_i, $\bar{Q}_1$, $\bar{Q}_2$, and $\bar{Q}_3$ corresponding to the point-in-time measures of the company's claim management process. The effective rate for *u*, *v*, *q* and a combination of them should be estimated. Then the hypothesis can be easily tested by referring the power value, which indicates the effectiveness of actions taken in each region. The proposed method is illustrated in section 4.2. The power values in terms of $\lambda N_i = 6.87$ for preferred sets of $\bar{Q}_1$, $\bar{Q}_2$, and $\bar{Q}_3$ of *u*, (*u*,*q*), (*v*,*q*), *v* and *q* were provided in the appendix table B1. The power values are calculated by developing R code for the LR test on the basis of the proposed likelihood function of the null and alternative hypotheses as outlined in this section.

3.6 Comparative analysis between the proposed method by Kano et al. (2013) and this thesis

According to the proposed method by Kano et al. (2013), a small number of claims indicates that action taken is effective. The "$m_{l,k}$" proposed by Kano et al. (2013) and "$1-\beta$" proposed method in this thesis are analyzed comparatively. It is assumed that grouped claim data is $m_{1,2}$ = 0 for region [1,2] and $m_{3,3}$= 0 for region [3,3]. In other words, actions taken for region [1,2] and [3,3] were completely effective and claims did not recur. They correspond to u = 1.0 for region [1,2] and $q = 1.0$ for region [3,3]. Based on the above setting, the proposed method "$1-\beta$" for λN_i, $\bar{Q}_1$, $\bar{Q}_2$, and $\bar{Q}_3$ is discussed.

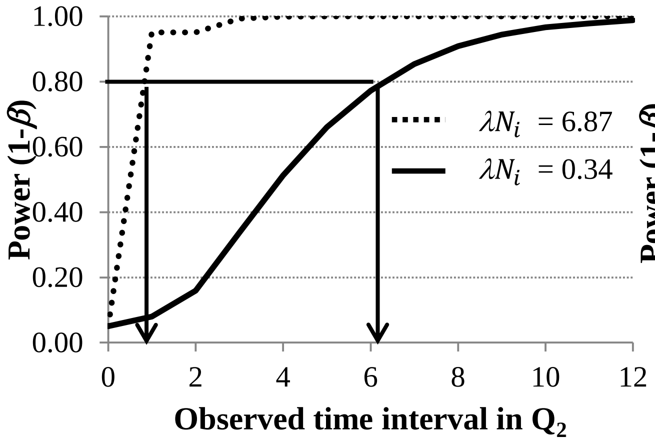

Figure 3.10 Power curves for λN_i = 0.34 for $\bar{Q}_1$ =2 and Q_2 for u =1.0 for α =0.05

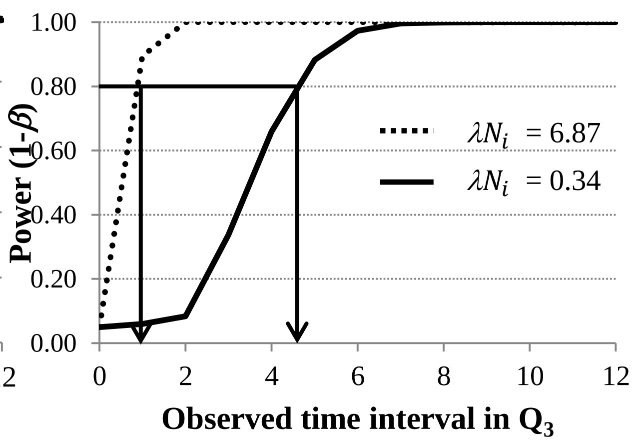

Figure 3.11 Power curves for λN_i = 0.34 for Q_3 for q =1.0 for α =0.05

Fig. 3.10 plots the power curves for λN_i = 0.34 and 6.87 for $\bar{Q}_1 = 2$ and Q_2 for u = 1.0 for α = 0.05. Fig. 3.11 plots the power curves for λN_i = 0.34 and 6.87 for Q_3 for $q = 1.0$. Generally the larger λN_i requires the smaller time interval to obtain an acceptable power value. For λN_i= 6.87, Q_2 less than 1 month in Fig.3.10 and Q_3 about 1 month in Fig.3.11 are required to obtain $1-\beta$ = 0.80. In contrast, for λN_i= 0.34, Q_2 about 6 months in Fig.3.10 and Q_3 less than 5 months in Fig.3.11 are required to obtain the same power value. As a result, the power value "$1-\beta$" which depends on λN_i, $\bar{Q}_1$, $\bar{Q}_2$, and $\bar{Q}_3$ shows the different conclusion even though u = 1.0 and q = 1.0 indicate that the actions taken are completely effective. The "$m_{l,k}$" proposed by Kano et al.(2013) and "$1-\beta$" proposed by this thesis show the same conclusion that the action taken is effective in case of expected number of claims per month and the length of time interval ($\bar{Q}_1$, $\bar{Q}_2$, and $\bar{Q}_3$) having some certain value under a particular power value i.e., λN_i= 0.34, $\bar{Q}_1$ =2 and $\bar{Q}_2$ = 6 for u = 1.0. Besides the above condition, in the case of λN_i being smaller and/or the length of time interval being shorter, power value becomes poor, which indicates that the action taken is ineffective.

Chapter 4

Application of the proposed methods

Overview

This chapter presents how companies should apply the proposed methods for detecting major quality problems and for examining effectiveness of actions taken. Two methods can be performed by simply using a statistical software program.

In Section 4.1, the operation procedures of the proposed methods are presented step-by-step. In Section 4.2, the proposed method for detecting major quality problems is illustrated. In Section 4.3, the proposed method for examining effectiveness of actions is illustrated. Example I is used for illustrating the case of which the two proposed methods are applied together and Example II is used for illustrating the case of which each method is applied independently.

4.1 Operation procedures for an implementation

4.1.1 Detecting major quality problems

1) Determine λ and N_i

2) Define a multiple of the null number of claims (ρ_g) which is needed for the detection.

3) Define a decision boundary (t*).

4) Determine an acceptable value of $(1-\beta(g))$ and/or ARL_0 as well as ARL_g

5) Choose a pair value of (ρ_1, h) which corresponds to 1) - 4) by using Table(s) in Appendix A.

6) Use ρ_1 to calculate CUSUM statistics in (2.12) and use threshold h in the CUSUM chart

7) Update the accumulated number of claims and plot the data on CUSUM chart.

8) Detect whether accumulated number of claims is out of control. If the number exceeds threshold h, register a major quality problem. If the number is below threshold h, the registration of a major quality problem is not needed.

4.1.2 Examining the effectiveness of actions taken

1) Group the number of claims $m_{l,k}$ and units shipped M_l corresponding to each region in the form of a QCMM.
2) Estimate $\mu_{l,k}$ except for $\mu_{1,1}$ by using (3.5).
3) Estimate $\mu_{1,1}$ by using (3.3).
4) Estimate the effectiveness of actions taken for each region by using (3.6- 3.10).
5) Determine the power value ($1-\beta$) by using Table(s) in Appendix B.
6) Determine whether the effectiveness of actions taken for each region was sufficient. If power value ($1-\beta$) is equal to or larger than the target value, the effectiveness was sufficient. Otherwise, there is not enough information to determine whether the actions taken were effective. For practical use, the power value ($1-\beta$) is marked with an "*". The markings can be represented in more detail. For instance, the company can further classify the level of significance into three categories by checking the different sets of ($1-\beta$): excellent with an "**" (($1-\beta$) ≥ 0.90), moderate with an "*" (0.50 ≤ ($1-\beta$) < 0.90), and poor with no marking (($1-\beta$) < 0.50).The power values in a QCMM and the marking are used to indicate the result of the determination.

4.2 Illustrated examples for detecting major quality problems

This section shows how to use monthly claim data for detecting major quality problems. CUSUM design parameters for the detection are provided for companies as shown in Appendix A. As an illustration, CUSUM design parameters in Table 2.3 are used for Example I and the appendix table A3 is used for Example II.

4.2.1 Example I

In Example I, the expected number of claims per month $\hat{\lambda}N_i$, was 6.87 during 5 months ($\hat{\lambda}$= 0.0055 and N_i = 1250). Claim data in Table 1.3 are used in this section. A multiple of the null number of claims (ρ_g) and a decision boundary (t*) for some specific values should be designed to obtain some acceptable value of $(1-\beta(g))$ and/or ARL_0 as well as ARL_g. Then a (ρ_1, h) can be used for identifying the multiple of the null number of claims at the decision boundary by observing cumulative claims represented in the CUSUM chart. If the number of claims exceeds h, the chart signals a major quality problem. By using Table 2.3, the detection of $\lambda_g N_i$= 8.59 ($\lambda_0 N_i$ = 6.87, $\rho_g =$ 1.25) by t* = 12 is selected. Based on three pair values of (ρ_1, h), one selection from them should be justified by considering the effects on customers and quality costs, which are related to ARL_0 and ARL_g. For illustration, the pair value of (ρ_1, h) = (1.50, 8.9) is selected because it shows an acceptable value of ARL_0 about 227 and ARL_g about 7 months. With this selection, ρ_1 is used in calculating in (2.12) and threshold h is used in the CUSUM chart. The cumulative claims for the first 5 months of units shipped in Table 1.3 are now considered. As shown in Fig.4.1, a signal of large increase was triggered within two months.

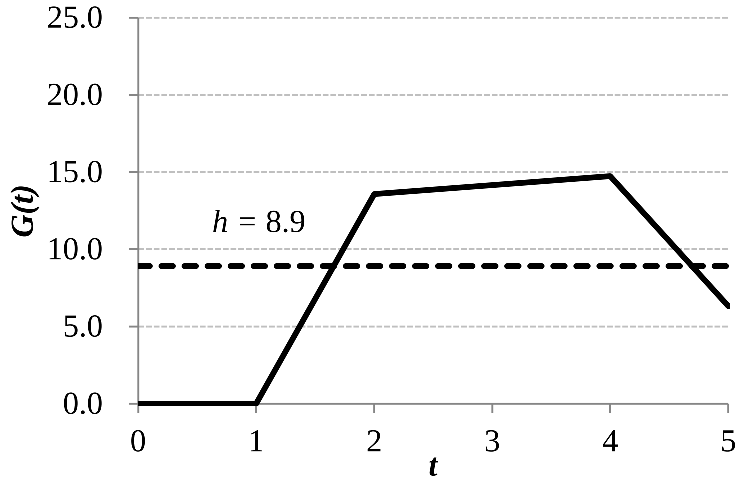

Figure 4.1 CUSUM chart with threshold h = 8.9 for Example I

Table 4.1 shows CUSUM statistics, $G(t)$ and h, which correspond to the plot in Figure 4.1. At the second month, $G(t)$ reached 13.58 which exceeds threshold h = 8.9.

Table 4.1 CUSUM statistics for Example I

t	$\sum_{t=0}^{t} n_t$	$W(t) - W(t-1)$	$G(t)$	h
0	0	0.00	0.00	8.9
1	0	-7.42	0.00	8.9
2	1	13.58	13.58	8.9
3	23	0.58	14.16	8.9
4	32	0.58	14.73	8.9
5	41	-8.42	6.31	8.9

From the results of the detection, an MQPR was defined at the second month, and the monthly claims were aggregated into time intervals for creating a QCMM as shown in Table 4.2. RPC occurred within four months after MR. After RPC, claim data was collected for one more months. RCO was not identified because recurrent claims were not occurred.

Table 4.2 QCMM for Example I

			1 month	1 month	2 months	1 month
		No. of unit shipped in the intervals	Time of claim occurrence			
			P1: MR - FCO	P2: FCO - MQPR	P3: MQPR- RPC	P4: RPC ~
Time of product shipment	P1: MR – FCO	1250	1	16	13	0
	P2: FCO – MQPR	1250	-	6	3	0
	P3: MQPR – RPC	2500	-	-	2	0
	P4: RPC ~	1250	-	-	-	0

4.2.2 Example II

In Example II, the expected number of claims per month λN_i was 0.34 (λ = 0.0017 and N_i = 200). Claim data in Table 1.2 are used in this section. As an example, CUSUM chart for 12 months is shown in Figure 4.2. By using the appendix table A3, the detection of $\lambda_g N_i$= 0.51 ($\lambda_0 N_i$ = 0.34, $\rho_g =$ 1.50) by t* = 24 is selected. In this case, a choice of (ρ_1, h) is selected based on a moderate power value (1$-\beta(g)$) of 0.70 which is specified by a certain company. The choice of (ρ_1, h) = (2.00, 6.2) that provides (1$-\beta(g)$) = 0.74 is selected. For this selection, threshold h = 6.2 is used. As shown in Figure 4.2, a signal that expresses a large increase was detected within four months. Table 4.3 shows CUSUM statistics, $G(t)$ and h, which correspond to the plot in Figure 4.2. Judging from the results of the detection, the registration of a major quality problem is not needed and the monthly claims were aggregated into time intervals for creating QCMM.

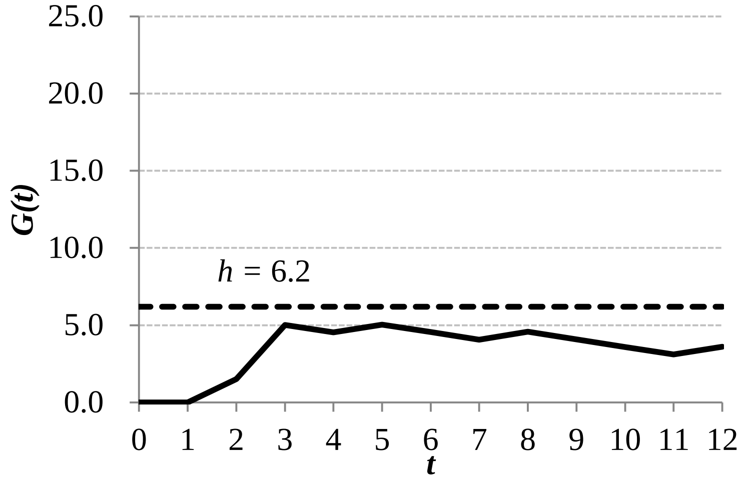

Figure 4.2 CUSUM chart with threshold h = 6.2 for Example II

Table 4.3 CUSUM statistics for Example II

t	$\sum_{t=0}^{t} n_t$	$W(t) - W(t-1)$	$G(t)$	h
0	0	0.00	0.00	6.2
1	0	-0.49	0.00	6.2
2	2	1.51	1.51	6.2
3	6	3.51	5.02	6.2
4	6	-0.49	4.53	6.2
5	7	0.51	5.04	6.2
6	7	-0.49	4.55	6.2
7	7	-0.49	4.06	6.2
8	8	0.51	4.57	6.2
9	8	-0.49	4.08	6.2
10	8	-0.49	3.59	6.2
11	8	-0.49	3.09	6.2
12	9	0.51	3.60	6.2

4.3 Illustrated examples for examining effectiveness of actions taken

This section shows how to use the grouped claim data over time intervals for examining the effectiveness of actions taken. In Example I, the monthly claim data which was presented for detecting major quality problems in Section 4.2 is aggregated over time intervals and is used in this section for examining the effectiveness of the actions taken. Example II is based on the assumption that MQPR is pre-defined by the company using any method and it presents the usage of grouped claim data over time intervals for examining the effectiveness of the actions taken independently. Tables in Appendix B provide the power value $(1-\beta)$ which are used for Example I and II respectively. The two methods, one is proposed by Kano et, al. (2013) and the other is proposed in this thesis are discussed by using two examples at the end of subsection.

4.3.1 Example I

In Example I ($\lambda N_i = 6.87$), from the results of the detection in Section 4.2.1, an MQPR was defined within two months of MR, as indicated by $\bar{Q}_1 = 2$. From the company's information, RPC was defined within two months of MQPR, as indicated by $\bar{Q}_2 = 2$. After RPC, the data were collected for one month as indicated by $\bar{Q}_3 = 1$. Having collected the claim data after actions were taken for specific time intervals Q_1 and Q_2, grouped claims $m_{1,2}$ and aggregate M_1 are used to estimate $\mu_{1,2}$. For time interval Q_3, grouped claims $m_{3,3}$ and aggregate M_3 are used to estimate $\mu_{3,3}$. Then the effective stop usage rate u and recurrence prevention rate q can be easily estimated. The remaining effective rates (v, (u, q), and (v, q), which correspond to regions [2,2], [1,3], and [2,3], respectively) are able to be treated in a similar manner. The power value $(1-\beta)$, the appendix table B1 is helpful for examining the effectiveness of actions taken.

By referring to grouped claim data in the form of QCMM as shown in Table 4.2, the estimates of the expected claim rates $\hat{\mu}_{1,1}$ = 0.0083 for region [1,1], and $\hat{\mu}_{1,2}$ = 0.0064 for region [1,2], $\hat{u} = (\hat{\mu}_{1,1} - \hat{\mu}_{1,2})/\hat{\mu}_{1,1}$ = 0.2 are obtained. By specifying $\bar{Q}_1$ = 2 and $\bar{Q}_2$ = 2, and looking up the power of $\hat{u}$ = 0.2 in the appendix table B1, a power value $1-\beta$ = 0.11 is obtained. The $\hat{\mu}_{3,3}$ of 0 gives $\hat{q}$ = 1.0 for region [3,3]. By specifying $\bar{Q}_3$ = 1 and looking up the power of $\hat{q}$ = 1.0, a power value $1-\beta$ = 0.89 is obtained.

The results for the remaining regions can be obtained by using the same procedure. The actual number of claims $m_{l,k}$ and overall results are shown in Table 4.4. The actions taken in regions [1,3], [2,2], and [2,3] are clearly effective and marked with an "**" as the corresponding power values (0.95, 0.94 and 0.95) respectively. These results indicate significant results concerning the recurrence prevention actions in region [1,3], stop shipment in region [2,2] and the combination actions of recurrence prevention actions and stop shipment in region [2,3]. The $\hat{q}$ for region [3,3] which is moderate and is marked with an "*" indicates that recurrence prevention in production process was effective. In contrast, the $\hat{u}$ for region [1,2] which is poor and has no marking indicates that the stop usage action was ineffective. From the obtained results, a company should take another action for the claims and the units shipped in region [1,2].

Table 4.4 QCMM of Example I and testing results

			$\bar{Q}_1$=2		$\bar{Q}_2$=2	$\bar{Q}_3$=1
		No. of units shipped in Q_l (M_l)	Time of claim occurrence			
			P1: MR - FCO	P2: FCO - MQPR	P3: MQPR-RPC	P4: RPC ~
Time of product shipment	P1: MR – FCO	M_1=2500			[1,2] $m_{1,2}$ = 13+3 $\hat{u}$ = 0.2 1−β = 0.11	[1,3] $m_{1,3}$ = 0 $\hat{u}, \hat{q}$ = 1.0** 1−β = 0.95
	P2: FCO – MQPR					
	P3: MQPR – RPC	M_2=2500			[2,2] $m_{2,2}$ = 2 $\hat{v}$ = 0.9** 1−β = 0.94	[2,3] $m_{2,3}$ = 0 $\hat{v}, \hat{q}$ = 1.0** 1−β = 0.95
	P4: RPC ~	M_3=1250				[3,3] $m_{3,3}$ = 0 $\hat{q}$ = 1.0* 1−β = 0.89

According to the proposed method by Kano et al. (2012), number of claims in each region is measured, a small number of claims means that action taken is effective. The "$m_{l,k}$" proposed by Kano et al.(2012) and "$1-\beta$" the proposed method by this thesis are analyzed comparatively. The results of the proposed method are discussed above and the results by the proposal of Kano et al.(2012) are discussed as follows. By referring to $m_{1,2}, m_{1,3}, m_{2,2}, m_{2,3}$ and $m_{3,3}$, it shows that actions taken for regions [1,3], [2,2], [2,3] and [3,3] are effective as shown in Table 4.4. However, the action taken for regions [1,2] is ineffective. Both two analysis methods, the proposed method by Kano et al. (2012) and mine, had a similar result in examining effectiveness of actions taken for all regions.

4.3.2 Example II

In Example II ($\lambda N_i =$ 0.34), MQPR and RPC were done by the company for four months, six months later from MR as indicated by $\bar{Q}_1 = 4$ and $\bar{Q}_2 = 2$. After RPC, data was collected for eight months as indicated by $\bar{Q}_3 =$ 8. The monthly claims in Table 1.2 were aggregated into time intervals, creating a QCMM as shown in Table 1.4. The actual number of claims $m_{l,k}$ and overall results are shown in Table 4.5. From the expected claim rates $\widehat{\mu}_{1,1}$ = 0.0043 for region [1,1] and $\widehat{\mu}_{1,2}$ = 0.0025 for region [1,2], $\hat{u} = (\widehat{\mu}_{1,1} - \widehat{\mu}_{1,2})/\widehat{\mu}_{1,1}$ = 0.4 is obtained. By specifying $\bar{Q}_1$ = 4 and $\bar{Q}_2$ = 2 and looking up the power of $\hat{u}$ = 0.4 in the appendix table B2, a power $1-\beta$ = 0.14 is obtained. The results for the remaining regions can be obtained using the same procedure. From the standpoint of the power value ($1-\beta$), the power values for regions [1,2], [1,3], [2,2] and [2,3] which are poor indicate that actions taken corresponding to those regions were ineffective. From the obtained results, a company should take other actions for the claims and the units shipped in region [1,2], [1,3], [2,2] and [2,3]. The proposed method provides comprehensive and significant information to examine effectiveness of the actions taken.

According to the proposed method by Kano et al. (2012), for example, $m_{2,2}$ = 0 indicates that action taken for region [2,2] is effective. The comparative analysis, the proposed method by Kano et al. (2012), $m_{2,2}$ = 0, and ours $1-\beta$ = 0.08, show a different result. In this case, if the company makes a conclusion not to take another action based on number of claims ($m_{2,2}$), some claims possibly recur.

Table 4.5 QCMM of Example II and testing results

			$\bar{Q}_1$=4		$\bar{Q}_2$=2	$\bar{Q}_3$=8
		No. of units shipped in Q_l (M_l)	Time of claim occurrence			
			P1: MR – FCO	P2: FCO – MQPR	P3: MQPR – RPC	P4: RPC ~
Time of product shipment	P1: MR – FCO	M_1=800			[1,2] $m_{1,2}=1$ $\hat{u}=0.4$ 1−β =0.14	[1,3] $m_{1,3}=3$ $\hat{u},\hat{q}=0.6$ 1−β =0.42
	P2: FCO – MQPR					
	P3: MQPR – RPC	M_2=400			[2,2] $m_{2,2}=0$ $\hat{v}=1.0$ 1−β =0.08	[2,3] $m_{2,3}=3$ $\hat{v},\hat{q}=0.6$ 1−β =0.28
	P4: RPC ~	M_3=1600				-

In conclusion, the "$m_{l,k}$" proposed by Kano et al. (2012) is useful in case of being large in expected number of claims per month (λN_i= 6.87) as shown in Table 4.4. In contrast, The proposed method "$1-\beta$" is effective in many practical settings in terms of the expected number of claims per month (λN_i), the effective rates for u, v, q and their combination as well as the length of time interval ($\bar{Q}_1$, $\bar{Q}_2$, and $\bar{Q}_3$).

Chapter 5

Concluding remarks

Overview

In this chapter the main contributions of the thesis are discussed in section 5.1.
Section 5.2 presents various extensions to the proposed methods for future research. Section 5.3 outlines a number of viewpoints for practical application.

5.1 Main Contributions

This thesis presents easy-to-use statistical methods for improving claim management. Kano et al. (2013) only focused on a general idea for identifying major quality problems. In addition, their method for evaluating effectiveness of actions taken is not statistical. This thesis proposes two statistical methods; one is Cumulative Sum Control chart (CUSUM) for detecting major quality problems and the other one is the likelihood ratio test using Quality Claim Management Matrix (QCMM) for examining effectiveness of actions taken.

Concerning the former statistical method, it is an application of CUSUM proposed by Lawless et al. (2012). CUSUM design approach is indispensable. Therefore CUSUM design parameters, which were neither investigated nor provided by Lawless et al. (2012) are investigated in Chapter 2 and then provided in Appendix A for easily drawing out a scheme of detection.

Concerning the latter statistical method, the grouped claim model is developed and the likelihood ratio test using QCMM is proposed. In addition, the properties of the proposed method are investigated in Chapter 3 and then power values are provided in Appendix B for easily testing the effectiveness of actions taken.

The thesis also illustrated the two proposed methods by using two application examples of two companies. This thesis showed a flexible way for an implementation by illustrating the case of which the two proposed methods are applied together as well as of which each method is applied independently (in Chapter 4). Each company may have a different claim data structure and/or availability of information, etc. The flexible options are useful for implementation in various situations depending on a company.

In order to implement the two proposed methods widely around the industrial world, CUSUM design parameters for detecting and power values for testing which are provided in Appendix A and B cover a wide range of expected number of claims per month and various numbers of months for which units have been shipped. Moreover, they can be applied to any quality problem and claim rate of products.

5.2 Implications for future research

Several ideas listed below will be helpful for future research.

1. When applying CUSUM procedures for detecting major quality problems, the number of units shipped each month (N_i) may be varied depending on a company. In such case, the properties of CUSUM are also various. Therefore, it is difficult to prepare CUSUM design schemes of detection in advance. However, they can be obtained by using a statistical software program. The determination of the schemes, with the provided probability of a signal under null and increased number of claims at some specific time, is based on Markov chain calculations which are provided in subsection 2.2.2.

2. By applying the method of CUSUM procedures for detecting major quality problem, number of claims is assumed to follow a Poisson distribution. If number of claims is follow non-Poisson behavior, it can be assumed as Negative binomial variable which allows for extra-Poisson variation. In such situation, CUSUM procedures could still be used.

3. This thesis mainly focuses on claims concerning product lifetime but not concerning safety. The two statistical methods are proposed based on the assumption that the claims fit a Poisson distribution. In the case of claims related to software which are concerning quality problems, if the claims fit a Poisson distribution, the two proposed methods can also be applied. However, this thesis cannot be stated that Poisson distribution is appropriate for the claims of software. It will be a future issue.

4. The method for detecting major quality problem was shown in subsection 1.6.1. Although the method for specifying the three parameters (λ_0, λ_1, λ_g) including N_i and I with LR a priori is stated in the first scenario, Baysian method or machine learning method in the third scenario may be one of the alternatives to detect the change of the above parameters. The properties of the two scenarios mentioned above would be compared in a future research.

5. When the number of units shipped each month (N_i) is varied and N_i is larger, this thesis cannot state that CUSUM properties are robustness in the above condition. It will be a future issue.

5.3 Implications for practical application

A number of viewpoints listed below will be useful for practical application.

1. CUSUM plan design is related to trade-off between two situations, one is to keep long ARL under in-control state and the other is to keep short ARL under out-of control state. In the other words, one is to keep low α and high $(1-\beta(g))$. The trade-off under the conflicted situations may be performed by considering economic impact. A simply linear loss function was proposed by Hawkins and Zambal (2003). Interested readers may refer to the explanation by Taguchi (1986).

2. The proposed method for detecting major quality problems in this thesis focuses on the claims concerning product lifetime which incurred high warranty cost and /or gave customers dissatisfaction. In the case of the claims concerning product lifetime and safety, the proposed method may be applied by combining the degree of claim rate and the degree of safety for detecting a major quality problem.

3. As mentioned in Section 1.1, claim data analysis is indispensable for improving claim management. Other processes and/or other analysis methods are also useful even though they are not focused in this thesis. Particularly, claim data analysis for predicting the claim rate within the remaining time period of the warranty length. The predicted claims indicate the potential products that need actions taken. There are many literatures related to this issue. The books by Brostrom (2012), Kleinbaum and Klein (2012) and Mills (2011) are highly recommended for a practitioner. A general idea of analysis and prediction on warranty claims was outlined by Kalbfleisch, Lawless, and Robinson (1991). The prediction methods based on early field failure warranty data were

discussed by Gurel and Cakmakci (2013), Lu (1998) as well as Wu and Akbarov (2012). The prediction methods based on field failure complaint/claim data and supplementary data were discussed by Leitao and Newton (1989), Zhou, Chinnam and Korostelev (2012). The prediction method based on the actual claim and supplementary data was proposed by Watcharathiansakul, Yamamoto, and Suzuki (2013).

4. In case of roof tile claims, there is a possibility of seasonal effect on the lifetime. However, because of the limitation of claim and supplementary data, this thesis did not analyze the seasonal effects on product lifetime. If claim and supplementary data related to seasonal effect on product lifetime are provided, the proposed CUSUM procedures can also be applied. The related articles are referred to Hiraga, Yamamoto, and Suzuki, K. (2014) as well as Wu and Meeker (2002).

Appendix

A ARL_0 and ARL_g corresponding (ρ_1, h), α = 0.05, (1−$\beta(g)$), ρ_g = {1.25, 1.50, 1.75 and 2.00} and $t*$ = {6, 12 and 24} for $\lambda_0 N_i$ and I for detecting major quality problems

Table A1: $\lambda_0 N_i$ = 0.34, I = 2

$t*$	ρ_1	h	$\lambda_0 N_i = 0.34$		ρ_g= 1.25		ρ_g= 1.50		ρ_g= 1.75		ρ_g= 2.00	
			α	ARL_0	1−$\beta(g)$	ARL_g	1−$\beta(g)$	ARL_g	1−$\beta(g)$	ARL_g	1−$\beta(g)$	ARL_g
6	1.50	3.7	0.05	53.6	0.130	24.6	0.240	15.2	0.371	11.0	0.506	8.8
	1.75	3.4	0.05	64.3	0.115	28.3	0.217	16.7	0.344	11.7	0.477	9.1
	2.00	3.3	0.05	79.8	0.100	32.7	0.194	18.5	0.314	12.6	0.444	9.7
12	1.50	5.0	0.05	98.0	0.182	36.1	0.371	20.3	0.576	14.1	0.749	10.9
	1.75	4.4	0.05	123.9	0.176	43.3	0.356	22.7	0.556	15.0	0.730	11.3
	2.00	4.2	0.05	135.7	0.169	47.2	0.342	34.6	0.539	15.6	0.713	11.5
24	1.50	6.8	0.05	214.9	0.249	56.4	0.548	28.2	0.802	18.7	0.936	14.1
	1.75	5.8	0.05	301.1	0.220	72.4	0.501	32.1	0.763	19.8	0.916	14.3
	2.00	5.4	0.05	340.2	0.207	81.2	0.476	34.6	0.739	20.5	0.902	14.6

Table A2: $\lambda_0 N_i$ = 0.34, I = 4

$t*$	ρ_1	h	$\lambda_0 N_i = 0.34$		ρ_g= 1.25		ρ_g= 1.50		ρ_g= 1.75		ρ_g= 2.00	
			α	ARL_0	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g
6	1.50	4.2	0.05	51.6	0.147	20.0	0.298	11.8	0.477	8.7	0.646	7.1
	1.75	3.8	0.05	58.9	0.144	22.2	0.293	12.6	0.470	9.0	0.639	7.3
	2.00	3.4	0.05	80.9	0.142	27.0	0.285	14.1	0.455	9.5	0.621	7.4
12	1.50	5.8	0.05	107.9	0.234	30.0	0.514	15.6	0.766	10.9	0.914	8.6
	1.75	5.2	0.05	134.1	0.215	35.5	0.479	17.1	0.734	11.3	0.895	8.8
	2.00	4.4	0.05	162.8	0.203	40.8	0.458	24.4	0.714	11.6	0.883	8.7
24	1.50	7.8	0.05	254.1	0.343	45.5	0.748	20.6	0.951	13.6	0.995	10.5
	1.75	6.6	0.05	296.2	0.313	53.6	0.704	22.0	0.933	13.7	0.992	10.3
	2.00	5.6	0.05	370.9	0.274	65.3	0.650	24.4	0.907	14.1	0.986	10.2

Table A3: $\lambda_0 N_i$ = 0.34, I = 6

$t*$	ρ_1	h	$\lambda_0 N_i = 0.34$		ρ_g= 1.25		ρ_g= 1.50		ρ_g= 1.75		ρ_g= 2.00	
			α	ARL_0	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g
6	1.50	4.4	0.05	43.2	0.156	16.0	0.326	9.5	0.522	7.0	0.698	5.8
	1.75	4.0	0.05	57.8	0.154	19.0	0.321	10.3	0.515	7.3	0.692	5.8
	2.00	3.7	0.05	71.2	0.145	22.1	0.299	11.3	0.484	7.6	0.659	6.0
12	1.50	6.6	0.05	118.8	0.247	26.7	0.574	13.2	0.838	9.2	0.958	7.3
	1.75	5.7	0.05	150.2	0.233	31.4	0.547	14.1	0.816	9.3	0.948	7.3
	2.00	5.0	0.05	165.3	0.218	35.8	0.514	15.3	0.788	9.5	0.935	7.2
24	1.50	8.8	0.05	303.1	0.381	39.7	0.832	17.0	0.984	11.2	0.999	8.7
	1.75	7.2	0.05	354.8	0.345	45.6	0.791	17.9	0.975	11.0	0.999	8.7
	2.00	6.2	0.05	390.5	0.310	50.9	0.741	19.5	0.960	11.3	0.997	8.3

Table A4: $\lambda_0 N_i$ = 5.0, I = 2

$t*$	ρ_1	h	$\lambda_0 N_i = 5.0$		ρ_g= 1.25		ρ_g= 1.50		ρ_g= 1.75		ρ_g= 2.00	
			α	ARL_0	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g
6	1.50	6.8	0.05	81.4	0.463	10.1	0.908	4.8	0.996	3.5	1.000	3.0
	1.75	5.0	0.05	88.9	0.411	11.9	0.865	5.0	0.991	3.5	1.000	2.9
	2.00	3.8	0.05	109.5	0.365	14.2	0.819	5.2	0.984	3.4	1.000	2.8
12	1.50	8.8	0.05	179.2	0.641	13.2	0.990	5.5	1.000	3.9	1.000	3.3
	1.75	6.6	0.05	184.5	0.536	16.7	0.972	5.8	1.000	3.9	1.000	3.2
	2.00	4.8	0.05	201.9	0.483	19.3	0.950	7.2	1.000	3.8	1.000	3.0
24	1.50	10.6	0.05	378.2	0.825	16.5	1.000	6.2	1.000	4.3	1.000	3.6
	1.75	7.8	0.05	413.7	0.696	21.9	0.999	6.5	1.000	4.1	1.000	3.4
	2.00	6.0	0.05	395.5	0.602	27.5	0.994	7.2	1.000	4.2	1.000	3.3

Table A5: $\lambda_0 N_i$ = 5.0, I = 4

$t*$	ρ_1	h	$\lambda_0 N_i = 5.0$		ρ_g= 1.25		ρ_g= 1.50		ρ_g= 1.75		ρ_g= 2.00	
			α	ARL_0	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g
6	1.50	7.0	0.05	85.6	0.583	8.0	0.977	4.3	1.000	3.47	1.000	3.1
	1.75	4.8	0.05	112.9	0.494	9.8	0.949	4.3	0.999	3.28	1.000	2.9
	2.00	3.4	0.05	194.1	0.421	12.6	0.909	4.5	0.998	3.19	1.000	2.7
12	1.50	9.0	0.05	189.3	0.796	9.9	1.000	4.7	1.000	3.75	1.000	3.3
	1.75	6.2	0.05	186.2	0.674	12.4	0.998	4.8	1.000	3.58	1.000	3.1
	2.00	4.3	0.05	335.6	0.577	16.6	0.990	5.6	1.000	3.44	1.000	2.9
24	1.50	10.8	0.05	364.8	0.943	11.6	1.000	5.1	1.000	4.00	1.000	3.5
	1.75	7.4	0.05	447.6	0.827	15.9	1.000	5.2	1.000	3.81	1.000	3.3
	2.00	5.3	0.05	588.0	0.726	21.8	1.000	5.6	1.000	3.68	1.000	3.1

Table A6: $\lambda_0 N_i$ = 5.0, I = 6

$t*$	ρ_1	h	$\lambda_0 N_i = 5.0$		ρ_g= 1.25		ρ_g= 1.50		ρ_g= 1.75		ρ_g= 2.00	
			α	ARL_0	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g
6	1.50	7.4	0.05	112.4	0.598	6.7	0.985	3.3	1.000	2.5	1.000	2.1
	1.75	4.8	0.05	219.9	0.493	8.0	0.961	3.7	1.000	2.3	1.000	1.9
	2.00	3.4	0.05	442.2	0.409	9.5	0.919	4.1	0.999	2.2	1.000	1.7
12	1.50	9.2	0.05	206.0	0.851	8.8	1.000	3.3	1.000	2.8	1.000	2.3
	1.75	5.8	0.05	309.9	0.712	10.4	0.999	3.6	0.999	2.5	0.999	2.0
	2.00	3.8	0.05	536.5	0.590	12.8	0.996	4.0	0.996	2.3	0.996	1.8
24	1.50	11.1	0.05	389.6	0.971	12.4	1.000	3.4	0.996	3.0	0.996	2.5
	1.75	6.9	0.05	528.7	0.877	14.3	1.000	3.7	0.996	2.7	0.996	2.2
	2.00	4.5	0.05	651.6	0.774	17.7	1.000	4.1	0.996	2.6	0.996	2.1

Table A7: $\lambda_0 N_i$ = 10.0, I = 2

$t*$	ρ_1	h	$\lambda_0 N_i = 10.0$		ρ_g= 1.25		ρ_g= 1.50		ρ_g= 1.75		ρ_g= 2.00	
			α	ARL_0	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g
6	1.50	7.4	0.05	88.5	0.631	7.5	0.989	3.6	1.000	2.8	1.000	2.5
	1.75	4.6	0.05	111.9	0.543	9.0	0.972	9.0	1.000	2.6	1.000	2.3
	2.00	2.8	0.05	121.9	0.482	10.6	0.948	10.6	1.000	2.7	1.000	2.3
12	1.50	9.0	0.05	188.8	0.822	9.0	1.000	3.9	1.000	3.0	1.000	2.7
	1.75	6.3	0.05	272.2	0.680	12.6	0.998	4.1	1.000	2.9	1.000	2.5
	2.00	3.8	0.05	206.0	0.624	13.8	0.994	4.9	1.000	2.8	1.000	2.4
24	1.50	11.0	0.05	422.7	0.945	11.0	1.000	4.3	1.000	3.2	1.000	2.8
	1.75	7.4	0.05	447.6	0.836	15.2	1.000	4.4	1.000	3.1	1.000	2.6
	2.00	5.3	0.05	590.6	0.730	21.6	1.000	4.9	1.000	3.1	1.000	2.5

Table A8: $\lambda_0 N_i$ = 10.0, I = 4

$t*$	ρ_1	h	$\lambda_0 N_i = 10.0$		ρ_g= 1.25		ρ_g= 1.50		ρ_g= 1.75		ρ_g= 2.00	
			α	ARL_0	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g
6	1.50	7.0	0.05	129.1	0.751	6.1	0.999	3.4	1.000	2.8	1.000	2.5
	1.75	3.8	0.05	217.3	0.631	7.6	0.995	7.6	1.000	2.6	1.000	2.3
	2.00	1.8	0.05	509.9	0.521	10.4	0.983	10.4	1.000	2.5	1.000	2.2
12	1.50	8.8	0.05	198.5	0.929	7.0	1.000	3.7	1.000	3.0	1.000	2.7
	1.75	4.6	0.05	327.7	0.819	8.7	1.000	3.4	1.000	2.6	1.000	2.3
	2.00	2.4	0.05	514.8	0.711	11.1	1.000	3.6	1.000	2.5	1.000	2.2
24	1.50	10.2	0.05	382.7	0.993	7.9	1.000	3.9	1.000	3.1	1.000	2.8
	1.75	5.6	0.05	503.6	0.944	10.2	1.000	3.6	1.000	2.8	1.000	2.4
	2.00	2.8	0.05	810.3	0.860	13.4	1.000	3.6	1.000	2.7	1.000	2.3

Table A9: $\lambda_0 N_i$ = 10.0, I = 6

$t*$	ρ_1	h	$\lambda_0 N_i = 10.0$		ρ_g= 1.25		ρ_g= 1.50		ρ_g= 1.75		ρ_g= 2.00	
			α	ARL_0	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g	$1-\beta(g)$	ARL_g
6	1.50	7.0	0.05	166.5	0.782	4.8	1.000	2.4	1.000	1.8	1.000	1.5
	1.75	3.8	0.05	287.8	0.624	5.5	0.997	2.6	1.000	1.6	1.000	1.3
	2.00	1.9	0.05	489.2	0.487	6.3	0.984	2.8	1.000	1.5	1.000	1.2
12	1.50	8.3	0.05	627.4	0.961	6.7	1.000	2.3	1.000	1.9	1.000	1.6
	1.75	4.1	0.05	707.3	0.844	7.1	1.000	2.3	1.000	1.6	1.000	1.3
	2.00	2.0	0.05	909.6	0.652	8.0	1.000	2.5	1.000	1.5	1.000	1.2
24	1.50	10.1	0.05	2196.4	0.998	12.2	1.000	2.3	1.000	2.1	1.000	1.8
	1.75	4.8	0.05	2220.5	0.965	12.4	1.000	2.3	1.000	1.7	1.000	1.4
	2.00	2.2	0.05	2243.6	0.835	12.8	1.000	2.4	1.000	1.5	1.000	1.2

B Power values in terms of λN_i for $\bar{Q}_1$, $\bar{Q}_2$ and $\bar{Q}_3$ of $u, (u,q)$, (v,q), v, and q for examining effectiveness of actions taken
taken

Table B1: λN_i = 6.87

		For regions [1,2], [1,3] and [2,3]					
		$\bar{Q}_2$ or $\bar{Q}_3$					
$\bar{Q}_1$	[1,2] u	1	2	3	4	5	6
$\bar{Q}_1$	[1,3] u, q						
$\bar{Q}_2$	[2,3] v, q						
1	0.2	0.09	0.09	0.09	0.11	0.12	0.13
	0.4	0.15	0.19	0.25	0.32	0.37	0.43
	0.6	0.28	0.41	0.55	0.66	0.76	0.83
	0.8	0.50	0.75	0.88	0.95	0.98	0.99
	1.0	0.90	1.00	1.00	1.00	1.00	1.00
2	0.2	0.08	0.11	0.13	0.16	0.19	0.22
	0.4	0.19	0.31	0.43	0.55	0.63	0.71
	0.6	0.41	0.67	0.83	0.92	0.96	0.98
	0.8	0.75	0.95	0.99	1.00	1.00	1.00
	1.0	0.95	0.95	0.99	1.00	1.00	1.00

	For regions [2,2] and [3,3]					
	$\bar{Q}_2$ or $\bar{Q}_3$					
[2,2] v	1	2	3	4	5	6
[3,3] q						
0.2	0.09	0.09	0.13	0.19	0.26	0.35
0.4	0.15	0.25	0.43	0.64	0.81	0.92
0.6	0.27	0.55	0.83	0.96	1.00	1.00
0.8	0.51	0.88	0.99	1.00	1.00	1.00
1.0	0.89	1.00	1.00	1.00	1.00	1.00

Table B2: λN_i = 0.34

		For regions [1,2], [1,3] and [2,3]														
		$\bar{Q}_2$ or $\bar{Q}_3$														
$\bar{Q}_1$	[1,2] u															
$\bar{Q}_1$	[1,3] u, q	2	4	6	8	10	12	14	16	18	20	22	24	26	28	30
$\bar{Q}_2$	[2,3] v, q															
2	0.2	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.09	0.09	0.09	0.10	0.10	0.10	0.11
	0.4	0.08	0.14	0.14	0.15	0.16	0.17	0.18	0.19	0.20	0.22	0.24	0.25	0.27	0.29	0.31
	0.6	0.10	0.20	0.24	0.28	0.32	0.35	0.38	0.42	0.45	0.49	0.53	0.56	0.60	0.63	0.65
	0.8	0.12	0.32	0.43	0.52	0.59	0.65	0.71	0.76	0.80	0.83	0.86	0.89	0.91	0.93	0.94
	1.0	0.16	0.51	0.77	0.91	0.97	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
4	0.2	0.08	0.08	0.08	0.08	0.09	0.10	0.10	0.11	0.12	0.12	0.13	0.14	0.15	0.15	0.16
	0.4	0.14	0.15	0.17	0.19	0.22	0.25	0.29	0.32	0.35	0.39	0.41	0.44	0.48	0.50	0.53
	0.6	0.20	0.28	0.35	0.42	0.49	0.56	0.62	0.68	0.73	0.78	0.81	0.85	0.87	0.89	0.91
	0.8	0.32	0.51	0.66	0.76	0.83	0.89	0.93	0.96	0.97	0.98	0.99	0.99	1.00	1.00	1.00
	1.0	0.51	0.91	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

	For regions [2,2] and [3,3]														
	$\bar{Q}_2$ or $\bar{Q}_3$														
[2,2] v															
[3,3] q	2	4	6	8	10	12	14	16	18	20	22	24	26	28	30
0.2	0.06	0.07	0.08	0.09	0.10	0.12	0.15	0.17	0.21	0.24	0.28	0.33	0.37	0.42	0.47
0.4	0.05	0.10	0.16	0.21	0.29	0.37	0.48	0.58	0.68	0.77	0.84	0.89	0.94	0.96	0.98
0.6	0.06	0.16	0.33	0.45	0.62	0.76	0.87	0.94	0.98	0.99	1.00	1.00	1.00	1.00	1.00
0.8	0.07	0.27	0.61	0.80	0.93	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1.0	0.08	0.66	0.97	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

References

1. Behrens, B., Wilde, I., and Hoffman, M. (2007): “Complaint management using the extended 8D-method along the automotive supply chain,” *Production Engineering*, Vol.1, pp. 91–95.
2. Biswas, P., and Kalbfleisch, J.D. (2008): “A risk-adjusted CUSUM in continuous time based on the cox model,” *Statistics in Madecine*, Vol.27, pp. 3382-3406.
3. Bosch, V.G. and Enriquez, F.T. (2005): “TQM and QFD: exploiting a customer complaint system,” *International Journal of Quality & Reliability Management*, Vol. 22, pp.30-37.
4. British standard. (2003). “Guide to data analysis, quality control and improvement using cusum techniques-Part4: Cusum methods for discrete (count/classified) data,” BS5703-4.
5. Brook, D. and Evans, D.A. (1972): “An Approach to the probability distribution of cusum run length,” *Biometrika*, Vol.59, pp.539-549.
6. Brostrom, G. (2012): “Event History Analysis with R,” CRC Press, New York.
7. Gandy, A., Kvaloy, J.T., Bottle, A., and Zhou, F. (2010): “Risk-adjusted monitoring of time to event,” *Biometrika*, Vol.97, pp.375-388.
8. Goel, A.L and Wu, S.M. (1971): “Determination of ARLand a contour nomogram for CUSUM charts to control normal mean,” *Technometrics*, Vol.13, pp.221-30.
9. Gurel, U., and Cakmakci, M. (2013): “Impact of reliability on warranty: A study of application in a large size company of electronics industry,” *Measurement*, Vol.46, pp. 1297–1310
10. Hawkins,D.M., and Olwell,D.H. (1998): “Cumulative Sum Charts and charting for Quality improvement,” Springer, New York.
11. Hawkins,D.M., and Zambal,K.D. (2003): “On small shifts in quality control,” *Quality Engineering*, Vol.16, pp.143-149.
12. Hawkins,D.M., Qiu, P. (2003): “The Change point model for statistical process control, *Journal of Quality Technology*, Vol. 35, pp.355-366.
13. Hiraga, T, Yamamoto,W. and Suzuki, K. (2014), “Nonparametric Modeling and

Optimal Maintenance using Online Monitoring in Environments with Seasonal Variation”, International Journal of Performability Engineering, Vol. 10, pp.83-93.

14. International Organization for Standardization. (2004). “Quality management – Customer satisfaction - Guidelines for complaint handling in organizations,” ISO10002.
15. Jiang, W., Shu, L., and Kwok-Leung, T. (2011): “Weighted CUSUM control charts for monitoring Poisson processes with varying sample sizes,” *Journal of Quality Technology*, Vol.43, pp.346-362.
16. John, A.S., and Richard, S.L. (1994): “Gaining a competitive advantage by analyzing aggregate complaints,” *Journal of Consumer Marketing*, Vol. 11, pp. 15 – 26.
17. Kalbfleisch, J.D., Lawless, J.F., and Robinson, J.A. (1991): “Methods for the analysis and prediction of warranty claims,” *Technometrics*, Vol. 33, pp. 273-285.
18. Kano, N., Boonthanom, S., and Merchant, P. (2013): “Quality claims management matrix and its application,” Proceedings of Asian Network for Quality Congress 2013, Bangkok, Thailand. QP 1-3.
19. Kleinbaum, D. G. and Klein, M. (2012): “Survival Analysis: A self learning text,” Springer, New York.
20. Iskandar, B.P., and Blischke, W.R. (2003): “Reliability and warranty analysis of a motorcycle based on claims data,” in Case studies in reliability and maintenance, Blischke, W.R. and Murthy, D.N.P.eds, Wiley, pp.623-656.
21. Lawless, J.F. (1998): “Statistical analysis of product warranty data,” *International Statistical Review*, Vol. 66, pp.41-60.
22. Lawless, J.F., Crowder, M.J., and Lee K.A. (2012): “Monitoring warranty claims with CUSUMS,” *Technometrics*, Vol.54, pp.269–278.
23. Leitao, A. L. F. and Newton, D.W. (1989): “Proportional hazards modeling of aircraft cargo door complaints,” *Quality and Reliability Engineering International*, Vol.5, pp. 229-238.
24. Lu, M. W. (1998): “Automotive reliability prediction based on early field failure warranty data,” *Quality and Reliability Engineering International*, Vol.14, pp. 103–108.
25. Meeker,W.Q. and Escobar,L.A. (1998): “Statistical Methods for Reliability Data,” John Wiley and Son, Canada.
26. Mills, M. (2011): “Introducing Survival and Event History Analysis,” SAGE, New York.
27. Page, E.S. (1954): “Continuous Inspection Schemes,” *Biometrics*, 41, 100–115.

28. Rodriguez, L., and Magari, R.T. (2004): “Establishing tolerance levels for customer Complaints,” *Quality Assurance*, Vol.11, pp.63–73.
29. Suzuki, K. (1985a): “Nonparametric estimation of lifetime distribution from a record of failures and follow-ups,” *Journal of the American Statistical Association*, Vol.80, pp.68–72.
30. Suzuki, K. (1985b): “Estimation of lifetime parameters from incomplete field data,” *Technometrics*, Vol. 27, pp.263–271.
31. Taguchi, G. (1986): “Introduction to Quality Engineering,” White Plains, New York: UNIPUB.
32. Watcharathiansakul M., Yamamoto Y., and Suzuki, K. (2013): “A Method for Statistical Analysis of Claims data for Building Materials Products,” Proceedings of Asian Network for Quality Congress 2013, Bangkok, Thailand, CE 3-5.
33. Woodall, W.H. (1993): “The statistical design of CUSUM charts,” *Quality Engineering*, Vol.5, pp.559-570.
34. Woodall, W.H. (1997): “Control Charts Based on Attribute Data: Bibliography and Review,” *Journal of Quality Technology*, Vol.29, pp.172-183.
35. Wu, H., and Meeker, W.Q. (2002): “Early detection of reliability Problems Using Information from Warranty Databases,” *Technometrics*, Vol.44, pp.120–133.
36. Wu, S., and Akbarov, A. (2012): “Forecasting warranty claims for recently launched products,” *Reliability Engineering & System Safety*, Vol.106, pp.160-164.
37. Wu, S. (2013): “A review on coarse warranty data and analysis,” *Reliability Engineering and System Safety*, Vol. 114, pp. 1–11.
38. Zhou, C., Chinnam, R. B., and Korostelev, A. (2012): “Hazard rate models for early detection of reliability problems using information from warranty databases and upstream supply chain,” *International Journal of Production Economics*, Vol. 139, pp. 180–195.

List of publications related to the thesis

Papers in Journals

1. Watcharathiansakul M., Yamamoto W., and Suzuki K. (2016): "Analyzing claim data for detecting major quality problems and examining effectiveness of actions taken", *Reliability Engineering Association of Japan*, Vol.38, No.6, pp. 389-406. (Related to a part of CH2 and CH3)

Papers International conference proceedings

1. Watcharathiansakul M., Yamamoto W., and Suzuki, K. (2013): "A Method for Statistical Analysis of Claims data for Building Materials Products", Proceedings of Asian Network for Quality Congress 2013, Bangkok, Thailand, CE 3-5, pp.1-9.
2. Watcharathiansakul M., Yamamoto W., and Suzuki, K. (2014): "Effective claim management using aggregated claim data and statistical analysis", Proceeding of the 6th International Conference on Quality 2014, V5-13, pp. 895-905.

3*. Watcharathiansakul M., Yamamoto Y., and Suzuki, K. (2016): "On monitoring customer claims using CUSUM procedure for QCMM", Proceedings of Asian Network for Quality Congress 2016, Russia, C6_JP30. (Related to a part of CH2 and CH4)

Domestic conference proceedings

4. Watcharathiansakul M., Yamamoto Y., and Suzuki, K. (2016): "An application of aggregate claims data analysis method for customer claim management", Proceedings of the 110th Research Conference, *Japanese Society for Quality Control*, 2016, pp. 45-48.
5. Watcharathiansakul M., Yamamoto Y., and Suzuki, K. (2016): "Analyzing claim data to detect major quality problems for QCMM", Proceedings of the 24th Spring Reliability Symposium, *Reliability Engineering Association of Japan*, 2016, pp.71-74.

Award

* Best Paper Award 2016 Sep.

The 14th ANQ (Asian Network for Quality) Congress 2016, Russia

Acknowledgements

First of all I would like to express my sincere thanks and appreciation to my advisor Prof.Kazuyuki Suzuki for his elaborated guidance and support during the entire course of this research. He not only guided me through this process but also provided various supports such as Japanese way of research, personal life and research circumstance in completion of my research at UEC. I am grateful for all of this help, guidance, and advice. I would also like to thank the other members of my advisory committee for their valuable advice and comments: Prof. Kenji Tanaka, Prof. Akihiko Ohsuga, Prof. Maomi Ueno, Prof. Ken Nishina, Nagoya Institute of Technology and Associate Prof. Shinji Yokogawa.

I really appreciate Prof.Noriaki Kano, professor emeritus of the Tokyo University of Science, who gave me good advice and suggestion before initiation of this research. I continue to feel his existence when developing my field of study.

I am deeply grateful to Dr.Watalu Yamamoto for his suggestions and assistance at every stage of my research. His insightful comments kept my research on the right track. In particular, I would like to express my gratitude to Associate Prof. Lu Jin for her cordial co-operation and support in many aspects of this research as well as kind advice for living happily in Japan.

I would like to show my greatest appreciation to the Center of Excellent Quality (CQD) at the Siam Cement Group (SCG) for providing the necessary funds for my Ph.D. and to our fellow SCG team members for their cooperation in this research.

I would also like to express my gratitude to the anonymous reviewers of Reliability Engineering Association of Japan for the valuable feedback and suggestions, which enabled me to significantly improve the quality of the paper.

Last but not least, I would also like to thank all of my family members, friends, and well-wishers for their continuous inspiration. Finally, I thank my husband, Mr.Narin Charoonwuthithum, for his endless love, encouragement, and understanding during my Ph.D.

Author’s biography

Ms. Meena Watcharathiansakul was born in Bangkok, Thailand, on March 01, 1978. She received Master of Engineering from Asian Institute of Technology, Thailand in 2007. In July 2007, she joined the QA Department of SCG Chemicals, Thailand, as a senior quality assurance engineer. In February 2012, she was awarded a SCG’s scholarship whose sponsor is the Center of Excellent Quality Development (CQD) at the Siam Cement Group (SCG). In March 2012, she entered the Doctor Course at the Graduate School of Information Systems, The University of Electro-Communucations, Tokyo, Japan. This thesis is the results of her research under the supervision of Professor Kazuyuki Suzuki who is a professor emeritus and a specially appointed professor at The University of Electro-Communications, Tokyo, Japan.